MEDINFO 2023 — The Future Is Accessible
J. Bichel-Findlay et al. (Eds.)

doi:10.3233/SHTI231082

Quality of Person-Generated Healthy Walking Data: An Explorative Analysis

Hyeoneui KIM[a,b,1], Eun-young IM[a] and Ga-in AHN[a]
[a] *College of Nursing, Seoul National University, Seoul, South Korea*
[b] *The Research Institute of Nursing Science, Seoul National University, South Korea*
ORCiD ID: Hyeoneui Kim https://orcid.org/0000-0002-5931-7286

Abstract. Despite the potential benefits of Person Generated Health Data (PGHD), data quality issues impede its use. This study examined the effect of different methods for filtering armband data on determining the amount of healthy walking and the consistency between healthy walking captured using armbands and health diaries. Four weeks of armband and health diary data were acquired from 103 college students. Armband data filtering was performed using heart rate measures and minimum daily step counts as a proxy for adequate daily wear time. No substantial differences in the filtered armband datasets were observed by filtering methods. Significant gaps were observed between healthy walking amounts determined from armband data and through the health diary. Future studies need to explore more diverse data filtering methods and their impact on health outcome assessments.

Keywords. Person-generated health data, wearable health data, data quality

1. Introduction

Person Generated Health Data (PGHD) refers to data created, recorded, or gathered by patients or caregivers to assist in the management of their health [1]. Wide utilization of personal wearable devices has accelerated the accumulation of PGHD. PGHD could improve healthcare services by providing more accurate information on our health and lifestyle [2]. Clinicians recognize the benefits of PGHD and welcome its inclusion in their clinical practice [3,4,5]. However, effective use of PGHD requires surmounting several obstacles related to data interoperability, data quality, workflow integration, and evidence generation [6]. Incorporating PGHD into the clinical process without attempting to resolve these challenges increase clinician burnout [7].

The quality and reliability of PGHD are of particular concern to clinicians. Recording Patient Reported Outcomes (PRO) or health history using questionnaires in health diary apps may involve individual subjectivity and memory-related issues [8]. Various device and connectivity-related technical problems and users' inadequacy in device wearing and setup are associated with the quality issues of biometric data passively collected through commercial wearable devices [9,10].

Despite the well-recognized quality issues regarding PGHD, there is no standardized method for the management and evaluation of PGHD quality. For

[1] Corresponding Author: Hyeoneui Kim, Address:103 Daehak-ro, Jongro-gu, Seoul, 03080, South Korea, email: ifilgood@snu.ac.kr, Tel: +82-02-740-8483.

example, in health care research what constitutes valid wearable health data differs among researchers or studies. Criteria for filtering wearable health data differ among studies, often based on daily wear time [11,12]. The lack of agreed-upon metrics for evaluating and describing the quality of wearable health data can hinder communicating and replicating the evidence generated through the studies, which is critical for facilitating the utilization of PGHD in patient care.

As a first step in developing an effective method of evaluating wearable health data, this study examined the effect of different data filtering criteria on the analysis of wearable health data, particularly in comparing "healthy walking" activities automatically captured via an armband and manually recorded in health diaries.

2. Methods

2.1. Data collection

This study was conducted with student volunteers recruited from a university in Seoul, South Korea, from July 1, 2020, to October 31, 2020. The participants were provided an armband device (Samsung Galaxy Fit 2) and instructed to collect activity data for four weeks. Samsung Health, a mobile app for Samsung wearable devices, was installed by participants to view and download their armband data. After participating for one month, participants downloaded their armband data and uploaded it to a secure server prepared for this study. An online health diary was also completed upon joining the study (baseline) and every week afterward for one month. This study was approved by the Institutional Review Board of the study site (IRB No. 2108/002-013).

2.2. Data preparation

We first determined the days when armbands were worn by participants for a sufficient time. Three types of filtering criteria were applied. The heart rate filter (HR8) removed the days, where the total duration of heart rate recording during waking hours (5 am ~ midnight) was less than 8 hours. By default, the wearer's heart rate was captured every 30 minutes by Galaxy fit2 during the resting period and more frequently during exercise. Two step count filters were applied: minimum daily step count of 1000 (SC1000) and 1500 (SC1500). Following the selection of the days regarded as having sufficient wear time, the second filtering step was applied to select participants with at least 20 days of armband data retained after the first step of filtering. In addition to tracking and storing every walking event, walking activities lasting more than 10 min were recognized by Galaxy Fit2 as healthy walking and maintained separately. Healthy walking data were extracted for the days that passed the data filtering steps.

Among various health behaviors and moods captured in weekly health diaries, this study used two items: "how many days during last week did you walk more than 10 minutes at once (healthy walking)?" and "what was the daily average healthy walking minutes of those days?" The weekly health diary recorded at least five days after the previous week's recording was considered valid. Data from the health diaries recorded for all four weeks were selected for analysis.

Alignment of armband data that passed the filtering step with health diary data was done based on dates. We searched the armband timestamps that matched the recording dates of health diaries. If no exact dates were identified, the next closest dates were selected. After aligning the armband data with the health diary data, we aggregated the armband data for the given week. Total and average healthy walking minutes for a given week were calculated, and the days that healthy walking was captured via armbands were counted (See supplementary file at http://shorturl.at/BDXY7).

2.3. Comparing healthy walking data between the armband and the health diary

A comparison of the average number of healthy walking days and healthy walking minutes each week between those calculated from armband data and those reported through health diaries was performed. These values were further summarized for each participant. The values did not show normal distribution when tested using the Shapiro-Wilk test ($p<0.05$); therefore, the significance of the differences in the values between armbands and health diaries was tested using the Wilcoxon signed rank test. Differences in average weekly healthy walking minutes and days were calculated by subtracting the values obtained from armband data from the values obtained from health diary data.

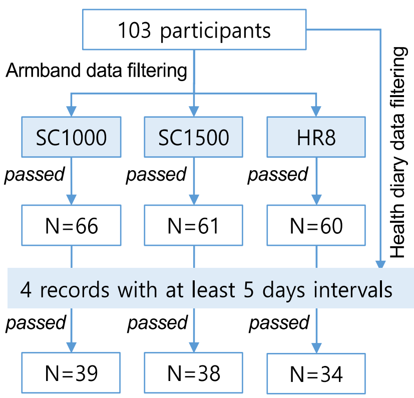

Figure 1. The samples retained after filtering (See the full-size graphic at http://shorturl.at/BDXY7).

3. Results

3.1. Data and data filtering results

The majority of the 103 student participants were females (n=68, 67%); the mean age was 25.32 (s.d.=4.72). Participants uploaded an average of 28 days of armband data (s.d.=7). The average daily duration of data collection varied from 14 minutes to 24 hours. The four weekly health diaries were completed by 97 participants.

Three filtering methods were used to process 2402 days of armband data. During the first filtering step, the HR8 filter removed 410 (17%) days of data. The SC1500 and SC1000 filters each removed 236 (9.8%) and 169 (7%) days of data. The second filtering step involved the selection of cases where at least 20 days of armband data were retained after the first step filters; datasets with the HR8, SC1000, and SC1500 filters were further reduced to 1,472 (61.3%), 1,780 (74.1%), and 1,640 (68.3%) days, respectively. Finally, the participants with health diary data that satisfied the health diary filtering conditions were selected. A summary of the number of participants retained in each data filtering step is presented in Figure 1.

3.2. Consistency in measuring healthy walking

The weekly average duration and days of healthy walking were compared among the datasets produced by the three armband filters. The SC1000 and SC1500 filters produced similar datasets, and no significant differences in healthy walking minutes and days were observed between the two filtering methods. The distributions of the differences in the weekly average healthy walking minutes and days between armbands and health diaries are shown in Figure 2. Overall, the health diary tended to report higher numbers of walking minutes and days than what was captured by the armbands. Using the Wilcoxon signed rank test ($p < 0.05$), statistically significant differences in the weekly average healthy walking minutes and days were observed regardless of the filtering methods applied to the armband data.

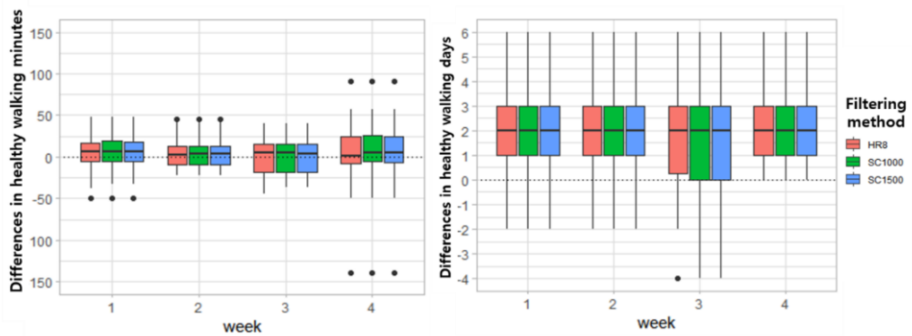

Figure 2. Differences in the weekly average health walking minutes and days (See the full-size graphic at http://shorturl.at/BDXY7).

4. Discussion

This study showed that more cases were dropped when HR-based wear time filtering was used, but the three filtering methods did not result in significantly different datasets. This study showed significant gaps in healthy walking minutes and days between the data captured by armbands and those entered into health diaries. Using the latter, there was a tendency toward overestimating minutes and days. Both measures have limitations, thus, determining which measure shows greater accuracy is difficult. For example, answering the questions included in the health diary required recalling walking activities of the past week that lasted at least 10 minutes and then calculating their averages and was therefore difficult. Indeed, questionnaire-based behavior health data thus often raise accuracy concerns. Most differences in the average weekly healthy walking minutes were within one hour. The differences in the number of healthy walking days varied widely but on average 2.2 days. Determining whether these differences are within acceptable ranges may depend on the purposes of data use. To gain better insights, studies examining the impact of these differences in relation to various data use cases are needed, for example, interpreting health outcomes or evaluating intervention effectiveness.

This study has several limitations. Data from small convenience samples and only three methods for filtering armband data were used. Furthermore, the filtering criteria utilized for armband and health diary data were somewhat arbitrary. Wear-time-based data filtering is relatively easy to apply and thus has been utilized in many studies. However, it does not address other factors threatening the quality of armband data.

5. Conclusions

This study delved into the impact of three distinct data filtering methods on the analysis of armband data. While the three quality filters did not yield statistically significant variations in the resulting datasets, this finding does not diminish the significance of employing standardized data quality management techniques. Forthcoming research endeavors need to explore a wider array of data quality management methodologies and broaden the assessment to encompass a more diverse range of data use cases.

References

[1] What are patient-generated health data? HealthIT.gov. Available from: https://www.healthit.gov/topic/otherhot-topics/what-are-patient-generated-health-data
[2] Omoloja A, Vundavalli S. Patient generated health data: benefits and challenges. Curr Probl Pediatr Adolesc Health Care. 2021 Nov;51(11):101103, doi: 10.1016/j.cppeds.2021.101103.
[3] Alpert JM, Manini T, Roberts M, Kota NSP, Mendoza T v, Solberg LM, Rashidi P. Secondary care provider attitudes towards patient generated health data from smartwatches. NPJ Digit Med. 2020 Mar 3;3:27, doi: 10.1038/s41746-020-0236-4.
[4] Wu DTY, Xin C, Bindhu S, Xu C, Sachdeva J, Brown JL, Jung H. Clinician perspectives and design implications in using patient-generated health data to improve mental health practices: mixed methods study. JMIR Form Res. 2020 Aug;4(8):e18123, doi: 10.2196/18123.
[5] Fonseka LN, Woo BK. Consumer wearables and the integration of new objective measures in oncology: patient and provider perspectives. JMIR Mhealth Uhealth. 2021 Jul;9(7):e28664, doi: 10.2196/28664.
[6] Tiase VL, Hull W, McFarland MM, Sward KA, Del Fiol G, Staes C, Weir C, Cummins MR. Patient-generated health data and electronic health record integration: a scoping review. JAMIA Open. 2021 Feb;3(4):619–27, doi: 10.1093/jamiaopen/ooaa052.
[7] Ye J. The impact of electronic health record-integrated patient-generated health data on clinician burnout. J Am Med Inform Assoc. 2021 Apr;28(5):1051-6, doi: 10.1093/jamia/ocab017.
[8] Foster A, Croot L, Brazier J, Harris J, O'cathain A. The facilitators and barriers to implementing patient reported outcome measures in organisations delivering health related services: a systematic review of reviews. J Patient Rep Outcomes. 2018 Oct3;2:46, doi: 10.1186/s41687-018-0072-3.
[9] Cho Y, Zhang H, Harris MR, Gong Y, Smith EL, Jiang Y. Acceptance and use of home-based electronic symptom self-reporting systems in patients with cancer: Systematic review. J Med Internet Res. 2021 Mar;23(3):e24638, doi: 10.2196/24638.
[10] Abdolkhani R, Borda A, Gray K. Quality management of patient generated health data in remote patient monitoring using medical wearables - a systematic review. Stud Health Technol Inform. 2018 Jan;252:1-7, doi: 10.3233/978-1-61499-890-7-1.
[11] Robertson MC, Green CE, Liao Y, Durand CP, Basen-Engquist KM. Self-efficacy and physical activity in overweight and obese adults participating in a worksite weight loss intervention: multistate modeling of wearable device data. Cancer Epidemiol Biomarkers Prev. 2020 Apr;29(4):769-76, doi: 10.1158/1055-9965.EPI-19-0907.
[12] Fendrich SJ, Balachandran M, Patel MS. Association between behavioral phenotypes and sustained use of smartphones and wearable devices to remotely monitor physical activity. Sci Rep. 2021 Nov;11(1) :21501, doi: 10.1038/s41598-021-01021-y.