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Validation of open-source step-counting algorithms for wrist-worn tri-axial accelerometers in cardiovascular patients

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ABSTRACT

Background: Accurate quantification of daily steps in a cardiovascular patient population is of high importance for primary and secondary prevention. While sensor derived step counts have been sufficiently validated for hip-worn devices and commercial wrist-worn devices, there is a lack of knowledge on validity of freely available step counting algorithms for raw acceleration data collected at the wrist.
Research question: How accurate are step-counting algorithms for wrist worn tri-axial accelerometers in a cardiac rehabilitation training setting?
Methods: Two step counting algorithms (Windowed Peak Detection, Autocorrelation) for tri-axial accelerometers (Axivity AX-3), were tested. Steps were recorded by chest-mounted GoPro video cameras as gold standard. Cardiovascular patients without neurological impairments enrolled in an ambulatory rehabilitation program were recruited. Recordings were performed during one 45–90 min outdoor physical therapy session of which 5-min segments of six movement categories, namely Walking, Running, Nordic, Stairs, Arm Movement [AM] With [+] and Without [-] Walking [W] were identified and analyzed. Mean absolute difference and mean absolute percentage error [MAPE] with regard to true steps measured from video are reported to report accuracy.
Results: Training sessions of 22 patients were recorded and analyzed. Steps were overestimated during AM-W and underestimated during Walking, Running and Stairs. Windowed Peak Detection algorithm was more accurate during AM+W and AM-W and Autocorrelation performed better during Nordic. A MAPE of close or below 10% was achieved by both algorithms for the categories: Walking, Running, Stairs and Nordic.
Significance: Both algorithms provided accurate results for estimation of step counts in a controlled setting of a cardiovascular patient population. The quantification of daily number of steps recorded by wrist-worn accelerometers delivering raw data analyzed by freely available algorithms is a cost-effective option for research studies.

1. Introduction

Cardiorespiratory fitness is a well-established and valid surrogate for cardiovascular (CV) risk in healthy people as well as in patients with CV disease [1]. A minimum of 150 min of at least moderate-intensity physical activity has been recommended to the general population as well as to CV patients to maintain health and prevent primary and secondary cardiovascular disease [2]. In addition, a minimum of 7000–10000 steps per day have been suggested to be appropriate for older adults as a general health recommendation [3–5]. Consequently, physical activity has been added to patient risk stratification for suffering a further CV event [6–8]. This has led to the increased clinical and scientific interest in the quantification of physical activity over the last two decades. With the technological progress in inertial sensors, the use of objective physical activity measuring devices like activity trackers, smartwatches and smartphone applications have recently become the assessment method of choice.

Several studies that have linked disease progression and activity levels and/or steps in CV patients already exist. One study in hypertrophic cardiomyopathy patients has found an association between disease severity and daily step count but not activity counts [9]. In addition, number of steps, physical activity and functional mobility have

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all been shown to be good predictors for hospital readmission or mortality in CV patients [10–13]. In a recent position paper on wearables, the European Society of Cardiology (ESC) has stated that there are still gaps in knowledge on methods or algorithms which translate data from continuous fitness trackers into meaningful information for primary and secondary prevention [14]. Therefore, there is increasing interest in identifying the best metrics to quantify physical activity by objective measuring methods. Furthermore, there is a need to determine the accuracy and validity of such accelerometer-based outcome measures.

There are several commercial devices (e.g., Fitbit, Garmin, Apple Watch, etc.) for measuring physical activity on the market. These products are equipped with displays and applications to motivate the user to be more active. Furthermore, there are devices with built-in algorithms for research on physical activity, like the Actigraph (ActiGraph Corp., USA) or the Geneactiv (Activeinsight Ltd., UK) movement sensors. Due to the built-in algorithms, these devices automatically calculate time spent in different activity zones as well as steps per day, which do not require any additional post-processing but are subject to smaller or larger errors depending on the measured activities [15–18]. Devices without built-in algorithms are cheaper but deliver only raw acceleration data, which need to be analyzed with external or custom-built algorithms. However, having access to the raw accelerometer data allows self-tailored data analysis that may be more appropriate to address specific study questions. One of the devices without built-in algorithms is the Axivity AX-3 (Axivity Ltd., Newcastle, UK), which is used in the UK Biobank study [19].

Several open-source packages are available to measure activity domains, e.g. by GGIR [20] and the UK Biobank algorithm [21]. Step counting algorithms are based on the time domain, the frequency domain, or machine learning. There have been several validation studies on new or improved step counting algorithms [22–24] and studies comparing different algorithms [25,26]. The current gold standard for step algorithm validation is video recording of the participants to determine the true number of steps. Many of these validation studies have focused on the correct detection of steps during standardized walking exercises in a laboratory. Only few studies have validated step-counting algorithms in a daily living setting [18,27,28], which is time consuming and tedious as large video files have to be watched and analyzed. The predefined acceptable limits for measurement accuracy in a laboratory setting is ± 3% and the acceptable limit for accuracy in free-living settings is ± 10% [29–31]. So far, step counting algorithms have been validated for the Axivity device worn at the lower back and the hip [15,27], but none have been validated for this device worn at the wrist. The accuracy of step algorithms is usually higher when measuring at the lower back, the hip, the thigh or the foot [25,32,33]. While wrist-worn devices have a lower accuracy for step measurements, they are more feasible for long wearing periods of several days or weeks [34,35].

The aim of the present study was to validate two different easily implementable and freely available step-counting algorithms for tri-axial wrist-worn accelerometer data (Axivity AX3) in the setting of a physiotherapy session of a cardiovascular rehabilitation program. Similar to a typical training session, 5-min bouts of different activities were assigned to defined movement categories. An open-source Windowed Peak Detection algorithm and an Autocorrelation algorithm were selected to derive steps from the raw acceleration signal. The sensor-derived number of steps was compared to the true amount of steps from the video recordings.

2. Methods

2.1. Subjects

This study was a prospective cross-sectional study, which has been approved by the Ethics committee of the canton of Berne (2020–01861). The study participants were recruited from the cardiac rehabilitation program at the Physiotherapy Department of the University Hospital Berne. Patients without neurological impairment, who participated in outdoor physiotherapy training sessions (45–90 min) were invited to participate in this study. All participants were informed about the study procedure and general data protection regulation prior to the session and signed a written informed consent.

2.2. Experimental procedure

Activities performed during the outdoor physiotherapy sessions included the following typical activities: walking (Walking), Nordic walking (Nordic); stair climbing (Stairs), arm movements while walking (AM+W), arm movements without walking (AM-W), and jogging (Running). The AM+W category mostly consisted of arm movements like arm swinging while walking, lifting knee to elbow and skipping. The AM-W mostly consisted of strengthening exercises such as push-ups on a wall, squats, and arm exercises with weights, but sometimes included a few steps in between exercises. The therapists devised their own programs for the training sessions.

2.3. Devices

A GoPro video camera (GoPro Inc., San Mateo, CA, USA) was mounted in front of the chest and pointed at the legs and feet of the participants (Fig. 1). The video images were recorded at 30 frames/s with 1080 pixels and with the field of view setting on wide. The training session was recorded as a continuous video file.

An Axivity AX-3 device (Axivity Ltd., Newcastle, UK) was worn on the non-dominant wrist and was set up with the open-source software AX3 GUI V43 [36] designed for Axivity devices. The devices recorded tri-axial acceleration of + /- 8 g at 50 Hz during the complete training session. The accelerometer time was synchronized with the computer

Fig. 1. GoPro camera setup.

time stamp during the device set-up.

2.4. Data processing

The video was scanned for one 5-min continuous or two 2.5-min continuous segments of each movement category. The beginning and end of each identified segments as well as individual steps during these segments were manually labeled with CowLog 3.0.2. [37], which is a video annotation tool that returns the corresponding timestamps of the labeling. The resulting file was then processed to display the steps per second for the segment of interest.

The raw acceleration data was exported as a .csv file using AX3 GUI V43. The raw unfiltered accelerometer data was resampled at 15 Hz using linear interpolation by the resample function from the GGIR R package (2.1–0), to reduce computational load. After resampling, the acceleration signal was used as input for two different step-counting algorithms.

2.5. Algorithms

2.5.1. Windowed peak detection

For calculation of steps from the acceleration signal, a Windowed Peak Detection (WPD) algorithm designed according to Gu et al. was used [22]. The WPD algorithm scans for peaks in the acceleration signal and applies various constraints, e.g. peak magnitude and distance to previous peak, to eliminate false peaks. The remaining peaks are counted as steps. The algorithm used can be found on GitHub [38] and is designed to be used in combination with the GGIR R package [20]. The default values of the algorithm were adjusted manually to improve the algorithm's accuracy during preliminary testing with 5 sequences of 1000 steps at different cadencies. The input variables for the algorithm and the components of the algorithm are illustrated as flow chart in Fig. 2.

2.6. Autocorrelation

As a second algorithm, an autocorrelation (AC) algorithm designed according to Rai et al. was used [24]. AC algorithms utilize the repetitive nature of walking. Windows of the signal are correlated with subsequent windows for different window sizes (resulting in different time lags) which are set according to prevailing frequencies in walking. If one of the calculated auto correlational coefficients surpasses a set threshold value, the movement state is identified as walking and the corresponding time lag is stored. The input variables were set according to preliminary testing. The components of the algorithm are visualized in Fig. 3. As a starting point, an algorithm from GitHub designed to work with Contiki microcontrollers was selected [39,40]. This algorithm was altered to run without the controller and to deliver the optimal time and the motion state as an output value. When the motion state was walking, two steps were calculated for every detected time lag.

2.6.1. Statistical analysis

The mean cadence was calculated by dividing the number of steps counted from the video file by the time for each bout of interest and expressed it as [steps/min]. For each segment, the difference in steps counted from video and the steps derived from the algorithms was computed. The mean difference as well as the mean absolute percentage error (MAPE) was calculated according to the following formula for each movement category and for each algorithm over the segments of all patients.

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_T} \right|$$

Where A_t indicates the true number of steps at time t (video) and F_t indicates the derived number of steps at time t (algorithms).

Additionally, the standard deviation (SD) and coefficient of variation (CV) was calculated for each movement category and algorithm. For the statistical analysis, R studio (Version 1.0.1093, R Studio, PBC) and R (4.0.3) was used.

3. Results

3.1. Participant characteristics

Twenty-two cardiac rehabilitation patients participated in the present study between February and April 2021. The study participants were a representative sample of heart patients performing ambulatory cardiac rehabilitation (unpublished data). The average age was 56.6 ± 9.0 years and the average BMI was 27.8 ± 4.9 kg/m^2. Peak VO_2, a measure of cardio-respiratory exercise capacity, was 22.1 ± 6.0 ml/min/kg, which corresponded to 87.5 ± 20.1% of the predicted value [41]. The most common reason for participation in the cardiac rehabilitation program was coronary heart disease with a recent coronary infarction (n = 16). Additionally, there were patients participating in a preventive rehabilitation during cardio toxic chemotherapies (n = 3), a patient with hypertensive cardiomyopathy (n = 1), a patient with valvular cardiopathy (n = 1) and one patient who suffered a type A aortic dissection (n = 1).

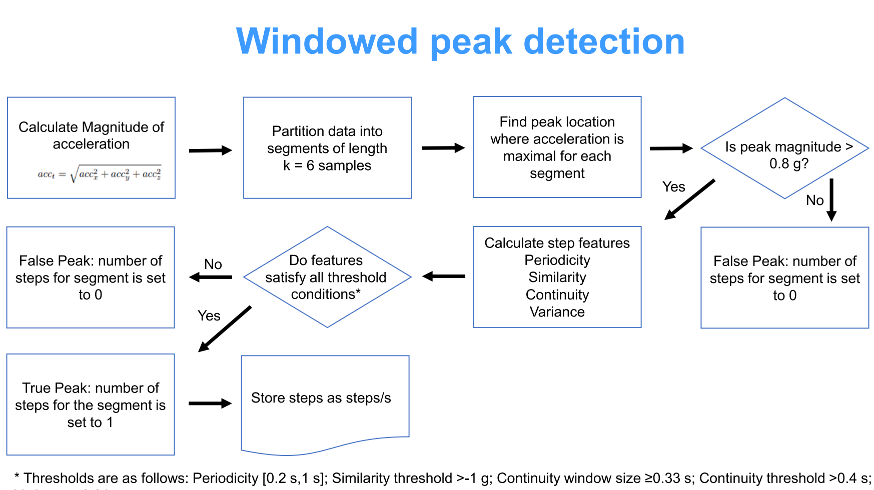

Fig. 2. Flowchart describing the Windowed Peak Detection algorithm.

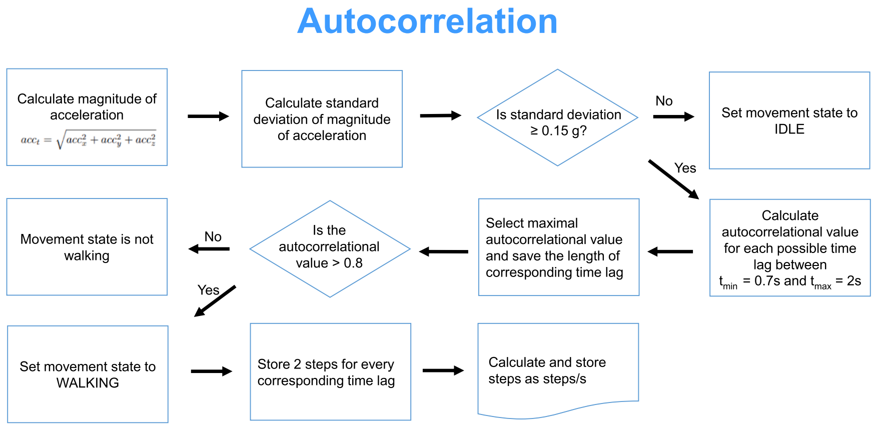

Fig. 3. Flowchart describing the Autocorrelation algorithm.

3.2. Movement categories and their physical intensity

Due to the individual exercise program of each physiotherapy session and the fitness level of the patient, not all movement categories were available for all patients. The number of available segments and mean segment length per movement category are shown in Table 1. The movement categories Walking, Stairs and Nordic had a mean cadence of over 100 steps/min which corresponds to at least moderate physical activity according to Tudor-Locke et al. [42]. The Running category corresponded to vigorous physical activity with a mean cadence of over 130 steps/min. Cadences for each movement category are displayed in Table 1.

3.3. Validation of step count

The differences of the number of sensor-derived steps to the gold standard are shown in Fig. 4. The results are given for both algorithms in each movement category. Differences in steps to the number of steps from the videos ranged from − 73–38 steps (−11 to 82%) for WPD and − 62–73 steps (−9 to 144%) for the Autocorrelation algorithm (Table 1). Steps were underestimated by both algorithms in the Walking, Running and Stairs movement categories and overestimated in the AM-W category. Derived number of steps by the WPD algorithm were lower than derived steps from the AC algorithm for all categories. For AM+W, steps were slightly overestimated by the AC algorithm, while the WPD algorithm was more accurate. Differences between algorithms were largest for Nordic for which the WPD algorithm underestimated the steps and the autocorrelation algorithm slightly overestimated the number of steps. Especially with the AC algorithm, the inter-patient variability was larger for the AM categories.

The MAPE for Running, Nordic, Stairs and Walking were below 10% for the AC algorithm (Table 1). For the WPD algorithm only the MAPE for Stairs and Walking were below 10%, while the MAPE for the Running and Nordic categories were slightly above 10%. The MAPE of both algorithms were significantly higher for tasks that contained arm movements, such as AM+W and AM-W. The MAPE for AM-W was inflated because of the significantly lower number of true steps (68) compared to the other movement tasks (540).

4. Discussion

This validation study of two step counting algorithms quantifying accelerations measured by wrist-worn Axivity AX3 during outdoor physical therapy sessions with cardiac patients showed relative accuracy with a MAPE of $<$ 10% for most movement categories. This study provides validity data for movements typical during daily living activities in middle-aged cardiac patients free from neurological impairment. The two step counting algorithms chosen based on simplicity and free availability can analyze any 3-dimensional raw acceleration data and our validity results are applicable to any wrist-worn device that measures 3-dimensional accelerations recorded at similar frequencies.

Both algorithms resulted in low errors for Walking. The Autocorrelation algorithm showed better accuracy for Stair, Nordic and Running than WPD, however, WPD was more accurate for movement categories including arm movements. The WPD algorithm is less likely to count false steps mainly due to the variance and magnitude threshold that is implemented by the WPD but absent in the Autocorrelation algorithm. However, it underestimates true steps when there are irregular peaks in the signal that do not originate from steps. For example, during Nordic walking the interaction of hand (pole insertion) and foot peak leads to irregular compound signals with peaks of double amplitude and some peaks in sequence with irregular phase shifts. These peaks of irregular amplitude lead to true peaks being marked as false peaks and an underestimation of steps. The Autocorrelation algorithm performs well during rhythmical activities such as walking at a steady pace. On the other hand, it tends to overestimate steps during activities with

Table 1
Absolute and relative difference to true number of steps (video recordings) for the two step counting algorithms and six movement categories. Shown are means (standard deviations).

	Video			Windowed Peak Detection		Autocorrelation	
Movement category (n)	True steps	Average segment length [s]	Cadence [steps/s]	Mean difference [steps]	MAPE [%]	Mean difference [steps]	MAPE [%]
Walking (20)	545 (90.7)	319.1 (52.6)	102.5 (6.9)	-14.9 (28.6)	4.1 (3.7)*	-19.2 (35.5)	5.8 (4.2)*
Running (5)	673 (168.9)	304.2 (63.2)	132.3 (13.3)	-73.4 (28.7)	11.2 (4.5)	-61.6 (32.4)	8.7 (3.1)
Nordic (14)	559 (48.2)	323.5 (24.3)	103.8 (8.2)	-57.0 (47.6)	10.9 (7.1)	4.5 (41.2)	5.2 (4.9)
Stairs (20)	536 (114.7)	304.4 (60.7)	106.5 (15.1)	-42.6 (37.9)	7.5 (5.7)	-27.7 (37.4)	6.4 (7.2)
AM+W (18)	386 (131.7)	312.5 (53.2)	73.5 (17.9)	-18.6 (71.9)	17.0 (13.0)	45.4 (99.1)	24.3 (24.7)
AM-W (22)	68 (45.3)	314.9 (48.5)	12.5 (7.5)	37.6 (58.5)	81.7 (76.0)	73.2 (70.6)	143.6 ± 128.4)

*Standard deviation of mean absolute percent error (MAPE) corresponds to the coefficient of variation (CV)
AM+W, arm movement while walking; AM-W, arm movement without walking

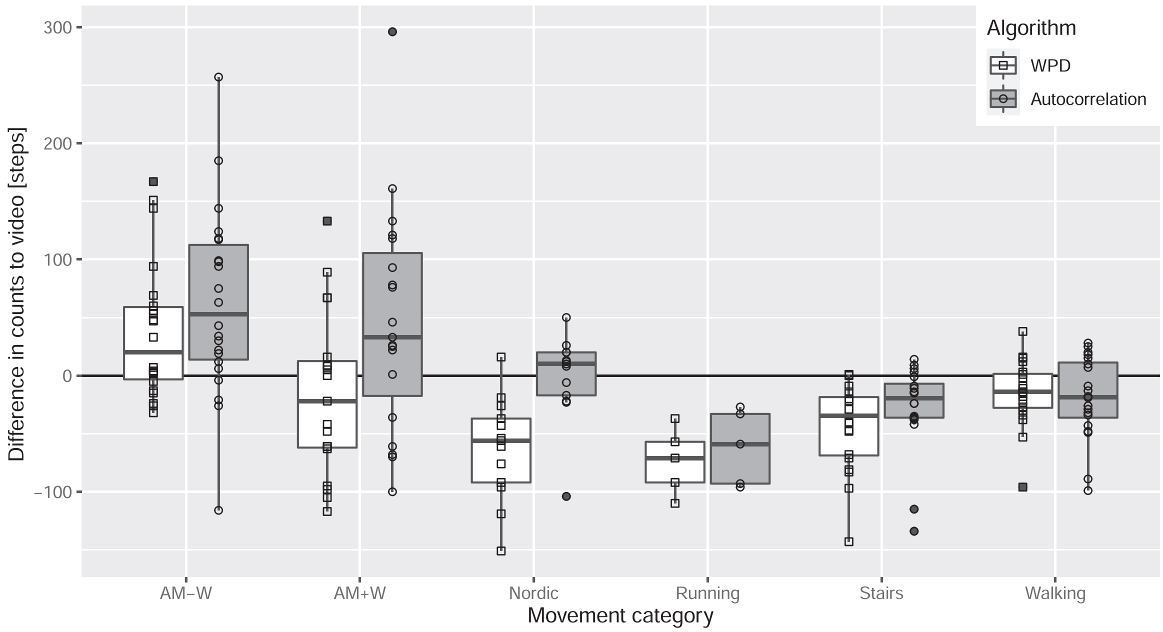

Fig. 4. Boxplot showing the absolute difference in steps of each algorithm to the gold standard for the different movement categories. Boxes show 1st to 3rd quartile and the whiskers extend from the hinges to the largest/smallest value within 1.5 interquartile range. The black bar in the boxes displays the median. Filled data points mark values outside the 1.5 interquartile range.

repetitive arm movements, which are performed at a frequency similar to walking frequencies. Both algorithms can be a valid option for quantifying number of steps, however, for research quantifying steps mainly during walking activities, an AC algorithm leads to more accurate results, while for research quantifying steps during activities that contain arm movements and irregular stepping movements, a WPD algorithm is better suited.

Our results are comparable to findings from literature. The study of Chen et al. investigated the accuracy of step counts from three commercial wristband monitors (Fitbit Flex, Garmin Vivo fit, Jawbone UP) during walking at different speeds, six different activities including stair climbing and two sitting tasks.[28] Our tested algorithms had comparable accuracies to the above-cited commercial devices during the walking and the stair climbing tasks, with all the commercial devices having an absolute percentage error (APE) ranging from 2.5% to 9.6% or lower for walking at different speeds. Both devices had an APE below 10% for stair climbing, with the Jawbone UP at the dominant wrist as an exception. Likewise, the commercial devices also overestimated steps during non-walking tasks with arm movements [28]. While this leads to an overestimation of true steps, number of steps is often used as surrogate measure of physical activity. Even in the absence of steps, arm movements constitute also a form of physical activity.

A recent review article of Fuller et al. summarized step counting validation studies with mostly wrist-worn commercial devices (including also studies on hip, collar-and ankle worn devices) [43]. Compared to their review, our tested algorithms scored similarly or slightly worse compared to the investigated commercial devices in a laboratory setting for normal walking tasks. With 91% of the commercial devices underestimating or overestimating steps with a mean percentage error (MPE) below − 3% or above + 3% and only 9% of the commercial devices having a MPE between − 3% and 3%. In a real-life setting, most of the commercial devices had a lower accuracy than the algorithms tested by us with 45% of the devices having a MAPE below 10% and 55% of the devices having an error higher than 10%.

The main limitations of this study was the setting of a physiotherapy session with activities of structured exercise which are not reflective of other activities of daily living. To assess the validity for daily-life activities, longer measurements in a real-life setting would be necessary. Additionally, the performance of the tested algorithms is specific for the gait speeds used in this study and cannot be applied to other speeds. Unfortunately, only few of our participants were fit enough to run, which is why the sample size for Running was small. Further, the standard deviation of the cadences during Walking was small and our results are not applicable to a more fragile or neurologic population with greater within-subject standard deviations of walking speed.

However, the analyzed movement categories contain different physical activity intensities and movements in a semi-constraint setting. There is more variability in the data compared to scripted movements in a laboratory setting, which makes the data more comparable to everyday activities than experiments in a laboratory setting. Both algorithms had good accuracy and low variance in the walking activity. Further, both algorithms showed a low error for all other movement categories. Consequently, both algorithms are valid alternatives for quantification of daily activity compared to commercial activity trackers.

5. Conclusion

In this study, an alternative to commercial devices for objectively measuring physical activity in cardiac patients for primary and secondary prevention was presented. For this purpose, two open-source algorithms adapted to a tri-axial accelerometer were tested and validated in outdoor cardiac rehabilitation training sessions. The tested algorithms resulted in sufficiently accurate calculation of steps in a cardiac patient population during structured physical exercise. The overestimated steps during movement categories with excessive arm movements may be more reflective of energy consumption rather than actual steps. Based on the diverse movement categories that were included, advantages and disadvantages of the two algorithms were shown.

Declarations of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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