J. Phys. Ther. Sci. 33: 621–626, 2021

The Journal of Physical Therapy Science

Original Article

Concurrent validity of the step time and walking speed obtained from the smartphone application CareCoaching in independent, community-dwelling older adults

Kensuke Oshima, PhD[1, 2)*], Tsuyoshi Asai, PhD[3, 4)], Hisumi Esaki[5)], Satoru Kameyama[5)], Junshiro Yamamoto[2)]

[1)] *Faculty of Rehabilitation, Kobe Gakuin University Graduate School: 518 Arise, Ikawadani-cho, Nishi-ku, Kobe, Hyogo 651-2180, Japan*
[2)] *EveRehab, Inc., Japan*
[3)] *Faculty of Rehabilitation, Kansai Medical University, Japan*
[4)] *Faculty of Rehabilitation, Kobe Gakuin University, Japan*
[5)] *ExaWizards Inc., Japan*

Abstract. [Purpose] In this study, we verified the validity of the step time and walking speed obtained from the smartphone gait analysis application CareCoaching. [Participants and Methods] The participants were 66 independent, community-dwelling adults aged 65 years or older who performed a 10-m walking test twice each under preferred- and slow-speed conditions. We concurrently measured gait motions using CareCoaching and the OptoGait system for reference data. Both systems compute walking speed and step time as gait parameters. We examined the concurrent validity of these parameters by using intra-class correlation coefficients (ICCs) and limits of agreement (LOAs) with Bland–Altman analyses. [Results] In the preferred walking speed condition, the ICCs of walking speed and step times between the CareCoaching and the OptoGait system were 0.67 and 0.93, respectively. In the slow walking speed condition, the ICCs for walking speed and step time were 0.78 and 0.97, respectively. In addition, the LOAs for step time were −0.0941 to 0.1160 for preferred walking speed and −0.0596 to 0.0883 for slow walking speed. The LOAs for walking speed were −0.4158 to 0.0568 for preferred walking speed and −0.3348 to 0.0523 for slow walking speed. [Conclusion] CareCoaching showed excellent agreement for step time and moderate-to-good agreement for walking speed in independent, community-dwelling older adults.

Key words: Two-dimensional video-based analysis, Smartphone gait analysis application, Older adults

(This article was submitted Mar. 12, 2021, and was accepted Jun. 6, 2021)

INTRODUCTION

Fractures due to falls are a major reason why older adults require long-term care (LTC). Not surprisingly, about half of these falls occur during walking[1)], indicating that evaluating gait ability is indispensable for falls prevention. However, properly conducting an observational assessment of gait-related falls risk can be difficult for LTC staff. Misjudging gait independence level can lead to an increased risk of falls or excessive physical activity restriction.

To manage such problems, an LTC facility requires a device that can simply and briefly assess gait ability. Although some higher accuracy gait analysis devices have been used in the laboratory and study field, such as a three-dimensional motion analysis system, these systems are difficult to apply in LTC facilities. Given this situation, ExaWizards Co., Ltd. (Minato-ku,

*Corresponding author. Kensuke Oshima (E-mail: ptkensuke@yahoo.co.jp)

Tokyo, Japan), has developed the smartphone and tablet application CareCoaching. This app computes walking speed and step time as gait parameters using a two-dimensional, video-based, skeleton extraction technology; just shooting a walking motion from the front plane will give gait parameters. However, to date, no studies have examined the validity of the gait parameters obtained from the CareCoaching system.

A previous systematic review has shown that some studies have reported the validity of a two-dimensional video gait analysis system as compared to a three-dimensional motion analysis device[2]. Most of these concurrent validity studies have computed gait parameters by shooting a walking motion from the sagittal plane. However, video analysis using the sagittal plane has two limitations for clinical settings. First, the sagittal plane requires a more secure video-shooting space than that needed to shoot from the frontal plane. Second, left–right motion cannot be measured. Clinically, performing an observational gait analysis from the frontal plane is important to assess mediolateral gait instability. However, few studies have examined the concurrent validity of the spatiotemporal gait parameters obtained from two-dimensional video analysis done from the frontal plane. Therefore, the computation algorithm for gait parameters in CareCoaching is a novel development with clinical applicability.

Therefore, the purpose of this study is to verify the concurrent validity of gait parameters obtained from CareCoaching as compared with the parameters obtained from the OptoGait system as a reference.

PARTICIPANTS AND METHODS

We designed a cross-sectional, concurrent, related-validity study. Participants were 66 community-dwelling adults ages 65 years or older who participated in a 1-day physical performance check-up at Kobegakuin University. Inclusion criteria were as follows: Participants (i) could walk alone with or without walking aids, (ii) did not have self-reported neurological disorders affecting their mobility or balance, and (iii) could obtain or give permission to shoot the videos.

We conducted this study with the approval of the Research and Ethics Committee for Humans at Kobegakuin University (20-06), and we gave each participant an oral and written explanation of the study's purpose and method and discussed the protection of their personal information. All individuals gave their consent to participate.

We measured gait as follows. We conducted a 10-m walking test twice each under the preferred- and slow walking speed conditions. We set the gait analysis section as the 5-m middle in a 10-m walkway including a 2.5-m acceleration and deceleration section. Because this section was short, we conducted multiple trials, as was done in previous studies[3–5].

For the preferred walking speed condition, we instructed the participants to "Walk straight until the marker tape at your own daily usual speed". For the slow walking speed condition, we instructed the participants to "Walk straight until the marker tape more slowly than your own usual walking speed". We used the CareCoaching and the OptoGait systems to obtain the gait parameters (see Fig. 1 for the settings for both systems).

CareCoaching is a video exchange smartphone or tablet app equipped with gait analysis. This system utilizes a two-dimensional, video-based, skeleton extraction technology that shoots a 10-m walking video from the frontal plane. CareCoaching estimates the 5-m long gait analysis by the time-varying rate of the vertical pixel length between the landmarks of the neck and middle of the left and right hip joints on the screen. This skeleton extraction, using original algorithms from ExaWizards Co., Ltd. (pose estimation based on the OpenPose machine learning library and environment detection), estimates the coordinates of the head, neck, shoulder, hip joints, knees, and feet on the screen pixels[6].

In this study, we mounted an iPad on a tripod at a height of 130 cm from the floor and 1 m from the start line (Fig. 1). We computed the gait parameters from the waveform-processed, skeletal-coordinate time series data. The screen resolution was 720p HD, and the sampling rate was 30 frames per sec (1/30th of a sec). We computed the step time as mean value using the time period between each peak point in the waveform obtained from the ankle joint location's time series data on the y axis. We calculated the walking speed as 5 m divided by the time to complete the estimated 5-m walk.

Previous studies have reported high validity and reliability for the OptoGait gait analysis device[3, 7]. This device, which has been used as a reference in a previous concurrent validity study[8], consists of a pair of transmission–reception 1-m bars equipped with 96 LED sensors at intervals of 1 cm. Walking between the transmitting–receiving bars arranged in parallel generates spatiotemporal data from the position information and time of the blocked LED sensor. The system's sampling rate is 1/1000th of a sec, and the spatial resolution is 1 cm. In this study, we set the OptoGait system with a measurement range of 5 m long × 3 m wide (Fig. 1) and defined the step time as the time from heel contact on one side to heel contact on the other side.

We measured motor function tests as sociodemographic data and conducted the Five Times Sit-to-Stand Chair Test (5CST) and the Timed Up and Go test (TUG). For the 5CST, we measured the sit-to-stand time from a modular pipe chair with a 45-cm seating height[9]. For the TUG, we measured the time to stand up from a seated position in the pipe chair, walking 3 m, turning around, walking back to the chair, and sitting down[10].

A self-administered questionnaire addressed sociodemographic data, fear of falling, and falls history. Sociodemographic measures included age, gender, height, weight, medical history, and number of medications. We obtained fear of falling using a single-item question: "Have you ever felt afraid of falling in your daily life?" Participants responded yes or no. We obtained participants' past 1 year falls history, asking "Do you have any history of falling in the previous year?" Participants answered yes or no. We defined *falling* as "an event that resulted in the participant unintentionally coming to the ground or other lower level".

We performed statistical analyses using commercially available software (JMP13.0; SAS Institute Japan, Tokyo, Japan). To verify the validity of the gait parameters of CareCoaching, we examined the agreement of these parameters obtained from the CareCoaching and OptoGait systems using intra-class correlation coefficient (ICC 2, 1) and the 95% limits of agreement (LOA) with Bland−Altman plot analysis. We computed the ICCs using the data of two trials together following the process of previous studies[3–5]. We calculated LOAs as follows: LOA = average of the absolute difference between both devices ± 1.96 × standard deviation (SD) of absolute difference between both devices. The criterion value of ICC to judge the level of agreement was followed by the previous study[11].

RESULTS

Table 1 shows the sociodemographic data for all study participants. Table 2 shows the means and SDs for the CareCoaching and OptoGait step time and walking speed, as well as their ICCs and LOAs.

In the preferred walking speed condition, the ICCs of walking speed and step times between the two systems were 0.67 and 0.93, respectively. In the slow walking speed condition, the ICCs of walking speed and step time were 0.78 and 0.97, respectively. In addition, the LOAs of step time were −0.0941 to 0.1160 for the preferred walking speed and −0.0596 to 0.0883 for the slow walking speed. The LOAs of walking speed were −0.4158 to 0.0568 for the preferred walking speed and −0.3348 to 0.0523 for the slow walking speed. In the Bland–Altman plot analyses, the red line indicates a difference between the two devices, and the red dotted line indicates the 95% LOA (Fig. 2).

DISCUSSION

We aimed to verify the concurrent validity of step time and walking speed for the CareCoaching system compared with

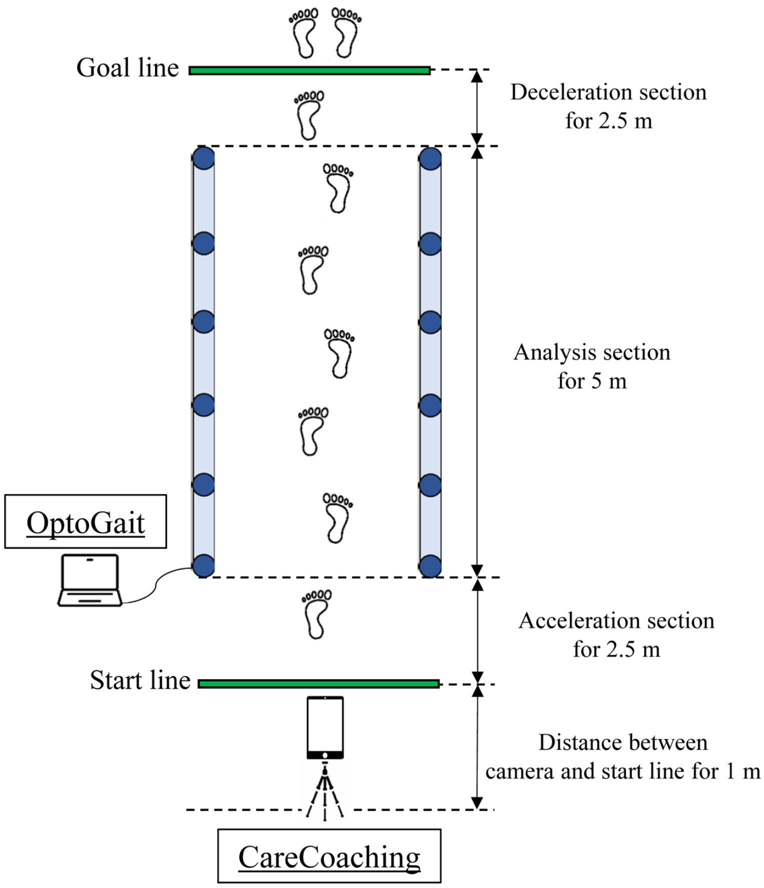

Fig. 1. Setup for gait parameter acquisition with CareCoaching and OptoGait.
OptoGait is shown in the two blue bars that longitudinally connect a pair of transmission−reception 1-m bars. CareCoaching is installed on the tablet terminal and mounted on a tripod at a height of 130 cm from the floor and 1 m from the start line. The analysis section of both devices is 5 m.

Table 1. Sociodemographic data for all participants (n=66)

Demographic	All participants Mean ± SD/ n (%)
Age (years)	73.7 ± 6.1
Female	37 (56%)
Height (cm)	155.7 ± 8.7
Weight (kg)	55.2 ± 9.9
Hypertension	15 (23%)
Diabetes mellitus	3 (5%)
Cardiovascular disease	4 (6%)
Respiratory disease	2 (3%)
No. of medications	1.7 ± 2.0
Five Times Sit-to-Stand Chair Test (sec)	7.11 ± 1.8
Timed Up and Go test (sec)	5.8 ± 1.2
Previous 1-year falls history	7 (11%)
Fear of falling	33 (50%)

Mean ± SD: mean ± standard deviation.

Table 2. Mean gait parameters for the study participants (n=66) and the concurrent validity of the gait parameters between CareCoaching and OptoGait

Gait parameters	CareCoaching Mean ± SD	OptoGait Mean ± SD	ICC (2,1)	Agreement level†	LOA‡
Preferred walking speed					
Step time (sec)	0.48 ± 0.04	0.49 ± 0.04	0.93	Excellent	−0.0941 to 0.1160
Walking speed (m/sec)	1.62 ± 0.26	1.44 ± 0.21	0.67	Moderate	−0.4158 to 0.0568
Slow walking speed					
Step time (sec)	0.57 ± 0.07	0.58 ± 0.08	0.97	Excellent	−0.0596 to 0.0883
Walking speed (m/sec)	1.21 ± 0.26	1.07 ± 0.22	0.78	Good	−0.3348 to 0.0523

Mean ± SD: mean ± standard deviation; ICC: intra-class correlation coefficient; LOA: limit of agreement.
†Agreement level was the reference values of ICCs to judge the level of agreement reported in a previous study[12].
‡LOA = average of the difference between both devices ± 1.96 × SD of the difference between both devices.

the OptoGait system as a reference. The results of the 5CST and TUG indicated that our study participants are independent, community-dwelling older adults.

We found that the ICCs of the gait parameters between the two systems were excellent for step time and moderate-to-good for walking speed according to the criterion[11].

The step times obtained from CareCoaching showed excellent concurrent validity with that of OptoGait in both walking speed conditions. The agreement between the two systems for slow walking speed was higher than that for preferred walking speed (ICCs 0.93 and 0.97, respectively). A previous study has investigated the concurrent validity of gait parameters obtained from a two-dimensional sagittal plane video analysis and from a three-dimensional motion capture system. The level of agreement for step time was excellent (ICC=0.998)[12]. Thus, although the concurrent validity of step time with CareCoaching in the slow-speed condition was similar to the results of the previous study, the validity under the preferred-speed condition was lower. In addition, the Bland–Altman plot analysis showed an underestimation error in step time, which increased from the measurement value to approximately <0.45 sec. These results indicate that the step time obtained using CareCoaching has an error depending on the walking speed.

Two factors may have led to this underestimation. First is the difference in sampling rate between CareCoaching and OptoGait: the rate of CareCoaching is 1/30th of a sec and that of OptoGait is 1/1000th of a sec. Thus, if the gait parameter is <0.33 or close to it, CareCoaching may have an error. Second, CareCoaching did not detect enough anatomical landmarks during the ground contact and toe-off phases. CareCoaching computed the step time using the time between each peak point in the ankle joint landmarks waveform consisting of the differences in adjacent sampling frequencies. Two-dimensional skeleton extraction by machine learning is always estimated in a state in which landmarks have slight fluctuations. Thus, the farther the analysis target is, the larger the error of estimation. Previous studies using similar technology have reported errors caused by lower sampling rate, fluctuations in estimated joint landmark locations, and increasing, and decreasing of the subject size on the screen[2, 12–14]. Therefore, when measuring step time with CareCoaching, we can calculate with high accuracy data for older adults with a slower walking speed (mean of 1.07 m/sec), but an underestimation can occur with older adults with a faster walking speed (mean of 1.44 m/sec).

The walking speed obtained from CareCoaching showed moderate-to-good concurrent validity with that from OptoGait. The agreement between the two systems in slow walking speed conditions was higher than that in preferred walking speed conditions (ICCs 0.67 and 0.78, respectively). A previous study has reported excellent concurrent validity of walking speed obtained from two-dimensional, sagittal plane video data (ICCs=0.972)[12]. Thus, our study indicates that the concurrent validity of walking speed obtained from frontal plane video data might be lower than that from sagittal plane video data. In addition, from the Bland–Altman plot, walking speed with CareCoaching was generally overestimated as compared to that of OptoGait. The Bland–Altman plot also showed that the faster the walking speed, the larger the overestimation error.

We consider that the cause of the overestimation is similar to the cause of the decreased ICCs in step time, such as a lower sampling rate and landmark location data fluctuation in skeletal extraction. We calculated the estimated walking speed from the time-varying rate of the number of pixels on the screen's *y* axis at the midpoints of the neck and both hip joints. Therefore, the estimated time taken to walk 5 m maybe be shortened because of the low sampling rate and slight landmark fluctuations by the skeletal estimation when the participant is far away. In addition, the Bland–Altman plot suggested that the walking speed in CareCoaching tends to be overestimated when exceeding approximately 1.0 m/sec.

To improve such issues, it is necessary to measure the sagittal- and front plane values with multiple cameras simultaneously and to increase the sampling rate. On the other hand, the Bland–Altman plot indicated that if the walking speed is

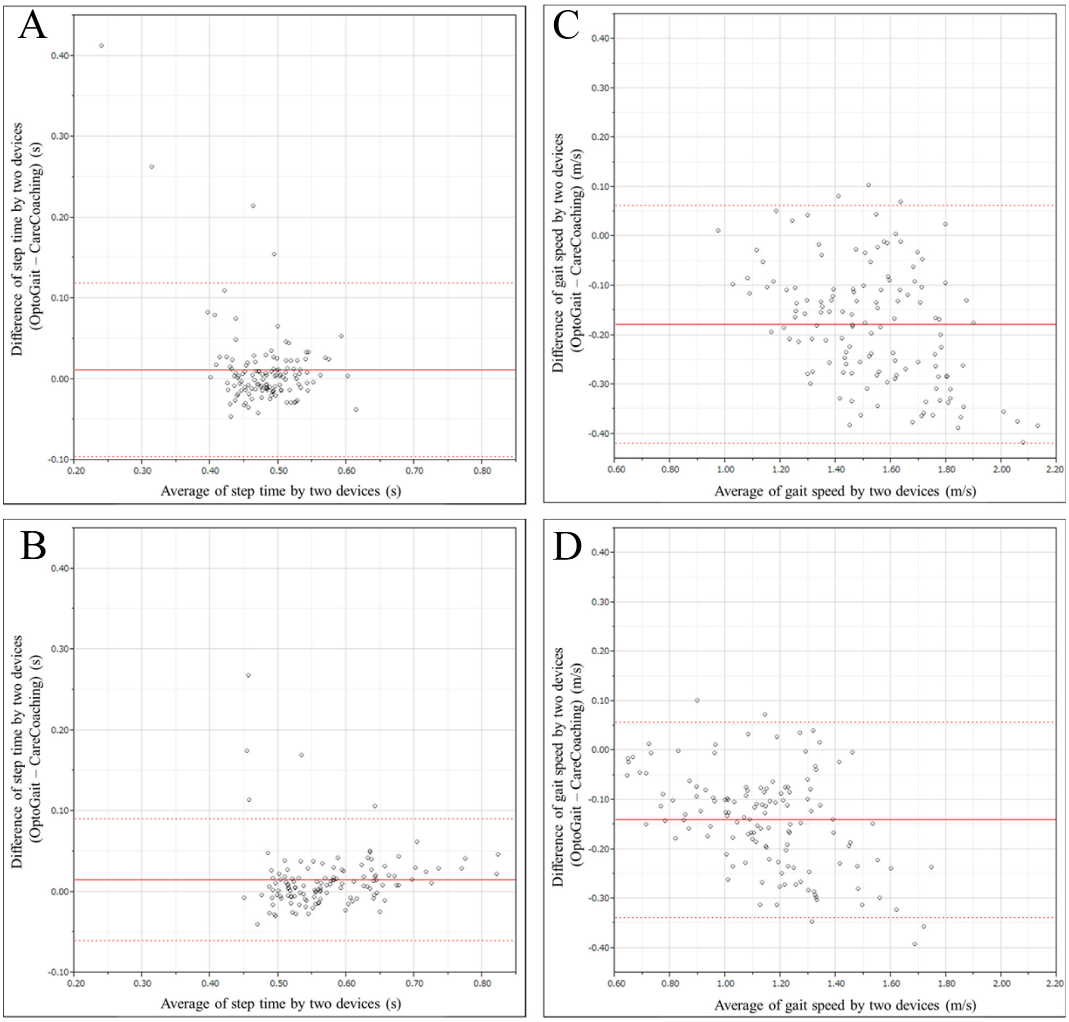

Fig. 2. Bland–Altman plots for CareCoaching and OptoGait of paired differences versus average.
A, Bland–Altman plots of step time in the preferred walking-speed condition. B, Bland–Altman plots of step time in the slow-speed condition. C, Bland–Altman plots of walking speed in the preferred walking-speed condition. D, Bland–Altman plots of walking speed in the slow-speed condition.

approximately <1.0 m/sec for both devices, the error between the two devices would decrease. However, our study cannot generalize the results to older adults who reduced their preferred walking speed to <1.0 km/sec. Therefore, further studies are needed for older adults requiring some physical care or social support.

To summarize, this study shows that CareCoaching can obtain excellent validity for step time and moderate-to-good validity for walking speed in independent, community-dwelling older adults. However, walking speed may be over interpreted in this type of individual. On the other hand, our results suggest that CareCoaching could obtain gait parameters with high validity in older adults with a walking speed of <1.0 km/sec. However, we cannot generalize these results. Therefore, further studies are needed using older adults requiring some physical care or social support.

Conflicts of interest

Everehab, Inc., and ExaWizards Co., Ltd. are in a relationship as business partners. Kensuke Oshima and Junshiro Yamamoto are employees of Everehab, Inc. Hisumi Esaki and Satoru Kameyama are employees of ExaWizards Co., Ltd. CareCoaching was developed by ExaWizards Co., Ltd.

ACKNOWLEDGMENTS

We acknowledge the contribution of the study participants and the volunteers for their time and positive participation. We thank Enago (www.enago.com) for the English-language editing performed on this work.

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