

An efficient study comparing the measure of spatiotemporal gait parameters between smartphone and insole sensors

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Abstract—Gait parameter assessment is important when determining participants' health status and developing therapeutic interventions. This paper discusses the smartphone technique design and implementation for measuring and studying participants' gait parameters. In this work, a new methodology is developed to study the spatiotemporal parameters of healthy people: step time, stride time, cadence and walking speed, using both insole sensors and smartphones. The purpose of this study is first to investigate the efficacy of a pair of Android smartphones (one for each leg) two Android smartphone as opposed to an insole sensor in determining spatiotemporal gait parameters. Second, the study evaluates the validity of a smartphone-based tri-axial accelerometer to assess gait characteristics. The spatiotemporal gait parameters of twenty healthy participants (10 male, 10 female, age >18) were assessed with insole sensors and smartphones. Each participant was asked to walk five trials. Data were collected from the insole sensors and the smartphones. Six statistic measures: Pearson correlation coefficient, linear regression, mean, standard deviation (SD), p-value, and Bland-Altman, were used to evaluate the validity of the smartphones. The correlation coefficient using the developed method ranged from 0.79 to 0.92 for both left and right legs. Based on the obtained results of the study with four parameters: step time,

stride time, cadence, and walking speed, it was observed that there was agreement between the smartphones and the insole sensors measuring gait parameters. Furthermore, these results demonstrated that the smartphone sensor is efficient in its measurement of the spatiotemporal gait parameters of healthy adult participants. Thus, it can provide reliable data without the need for expensive devices. Finally, the developed method may help an expert to objectively and effectively evaluate gait.

Keywords—smartphone, spatiotemporal, insole sensor, standard deviation (SD)

I. INTRODUCTION

The study of human gait is considered to be a significant component of medical diagnosis related to many aspects of people's health. The insights into human gait have many applications in exercise training and, therefore, in rehabilitation and therapy [1-3]. Different factors, such as pathological disease or injuries, may have an effect on the people's walk or locomotion, either permanently or temporarily [4]. Spatiotemporal gait parameters are related to adverse health issues such as risk of falls [5, 6]. Recently, gait analysis researchers have used different instruments to evaluate gait parameters to

study the risk of falling. Several technologies use insoles for specially designed shoes [7]. An insole sensor was shown to be suitable to determine human movement parameters such as the stance and swing phases [8]. The insole sensor is also able to measure a number of spatiotemporal gait parameters: swing time, stride length, step time and cadence [9]. Other studies using an insole pressure sensor data enable the planning of ways to reduce plantar pressure among diabetic patients [10].

A smartphone application has shown that an accelerometer sensor can be used for gait parameter analysis. The smartphone has been demonstrated to be an effective tool for monitoring human movement [11]. Other studies have shown that a smartphone-based fall detection system may be used for such different problems as fall detection [12] and rheumatoid arthritis [13].

[14] developed a method to validate the smartphone-based accelerometer for quantifying spatiotemporal gait parameters with other gait analysis devices such as GAITRite. In their study, 34 participants were recruited. Participants walked at slow and fast speeds over a 10-m distance while carrying a smartphone. Parameters such as step length, step time, gait velocity, and cadence were determined using smartphone-based accelerometers and then the study was validated with GAITRite. Their results were evaluated using the correlations coefficient (CC). An average CC between the smartphone-based and GAITRite-based systems was 0.89, 0.98, 0.96, and 0.87 for step length, step time, gait velocity, and cadence, respectively.

[15] presented a method to evaluate the concurrent validity of a smartphone. In that study, 16 healthy participants were used and the smartphone was attached first to the lower back and then to the sternum. Then, the reference standard and the smartphone were used to record vertical ground reaction forces and vertical acceleration. In this

study, the correlation coefficient and standard error were used to evaluate the proposed method. A strong reliability ($ICC \geq 0.75$) was reported, showing Pearson correlation coefficients between vertical ground reaction forces and vertical acceleration. The authors concluded that the smartphone could be used as a reliable and valid tool for the quantification of the sit-to-stand movement in healthy seniors.

More recently, [16], proposed a reliable and efficient method to assess spatiotemporal gait parameters using smartphone data based on an accelerometer and 3000E F-scan. In this study, 10 healthy adults walked three times with two smartphones and two insole sensors attached. Three parameters: step time, stride time, and cadence were calculated. The study reported that the smartphone accelerometer sensor could be an effective and efficient tool for assessing gait.

Current validation data for smartphone usually use only one phone to assess gait parameter. Furthermore, these studies have employed one or two assessment tools to evaluate performance results. Thus, the purpose of this research is to: (1) investigate two Android smartphones for determining spatiotemporal gait parameters (step time, stride time, cadence and walking speed) and (2) evaluate the validity of a smartphone-based tri-axial accelerometer to assess gait characteristics.

II. RESEARCH METHODOLOGY DESCRIPTION

In this work, 20 healthy participants were recruited for the proposed method to study the spatiotemporal parameters: step time, stride time, cadence, and walking speed of the insole and smartphone for healthy people.

A. Participants

The twenty healthy adult subjects (10 males, 10 females) were aged between 20 and 40 years. The other characteristics of the 20 subjects were mass and height 60 to 95 kg and 156 to 180 cm, respectively. All subjects were able to walk continuously for at least ten meters without help or assistance devices. Some demographic information was obtained from each participant; namely age, gender, height, weight and shoe size. All subjects gave written consent at the beginning of the trials. A human ethics application was approved by the Human Research Ethics Committee at the University of Southern Queensland.

B. Equipment

In this study, each subject wore an insole sensor 3000E F-scan in suitably sized shoes, connected to a computer to capture the data through the software F-Scan research. At the same time, each subject wore two smartphones, both Samsung Galaxy S9, which has a height of 5.81" (147.7 mm), width of 2.7" (68.7 mm), depth of .33" (8.5 mm), weight of 163 g and screen size of 5.8" (147.3 mm). The smartphones were placed on both legs as shown in Fig 1, a and b. Smartphones

were placed here because the upper area of the human body is complicated; thus, the process of obtaining accurate estimates is very difficult.

Fig 2 shows an example of one-step starting from the left side with heel strike, flat foot, midstance and toe off. All subjects walked along a 9 m straight pathway, with all gait measuring devices (insole shoes and smartphones) attached, five times. Each time (trial), the data were recorded individually for each device and each leg. Participants were asked to walk normally, and to start and stop walking when they heard the tester's instructions.

C. Procedures

In this work, an efficient method was used to study the spatiotemporal parameters of healthy people with the insoles and smartphones and to analyse and compare of spatiotemporal gait parameters between smartphone and insole sensors. The researcher followed a set procedure. Each participant signed a consent form. Next, explain the walking way, start and end point and how to hold the wires of the insole sensors to each individual. Then, data was recorded for all the participants. They were asked to start and stop walking when they heard the instructor



a. Subject wore insole sensors with



b. Insole sensor

Fig.1. a and b show an example for one person who wore insole sensors and smartphones during the test

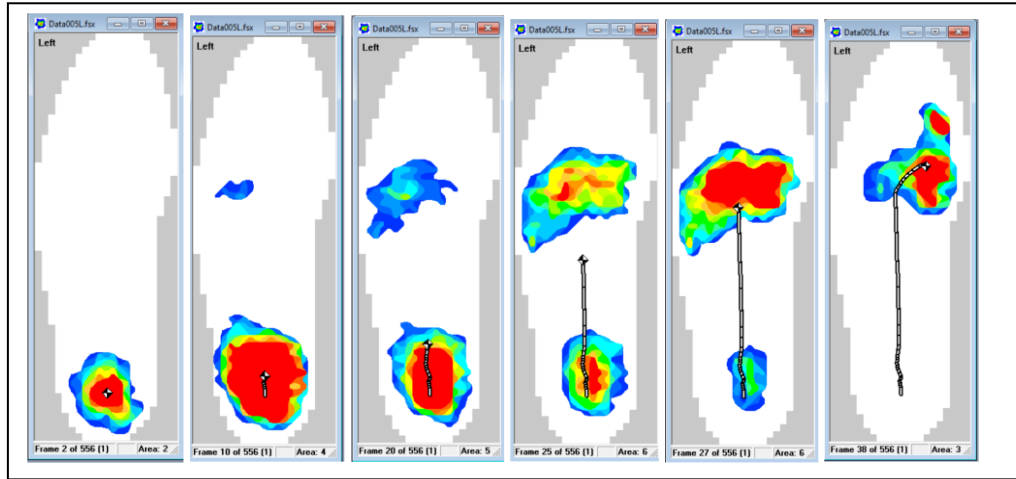


Fig.2. An example of flat foot, midstance and toe off pressure characteristics

give the instruction.

D. Data collection and processing

Reliable data were sought for the gait spatiotemporal parameters: step time, stride time, cadence and walking speed used in the study. Each subject's foot strike location was verified to ensure it was on the right way in the shoes after choosing the correct shoes size. Each trial represented the average time for three middle steps (from steps 5-7). From the foot pressure map obtained by the Tekscan data and the plots from the smartphone accelerometer, the three middle steps were used to calculate the stride time, step time and cadence, as shown in Figs. 3 a and b.

The acceleration data for nine steps in the normal walk are presented in Fig 4. The test for device, smartphone and insole sensors, were completed at the same time. The difference between them was observed. We noticed these differences in the patterns for the insole sensor and accelerometer sensor such as the noise and negative signal in accelerometer sensors but nothing like that in the insole sensors reading. In addition,

E. Statistical analysis

Blind-Altman plots were used to provide the bias and limit of agreement (LOA) between smartphone sensor and insole sensor data as well as to evaluate the developed study method.

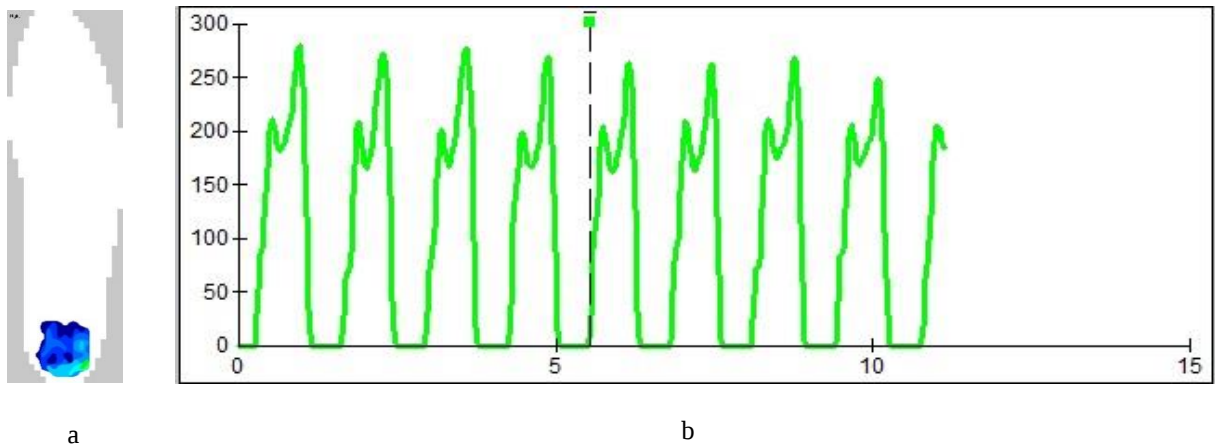


Fig.3. a and b show the heel strike insole sensor and heel strike for the fifth step, respectively

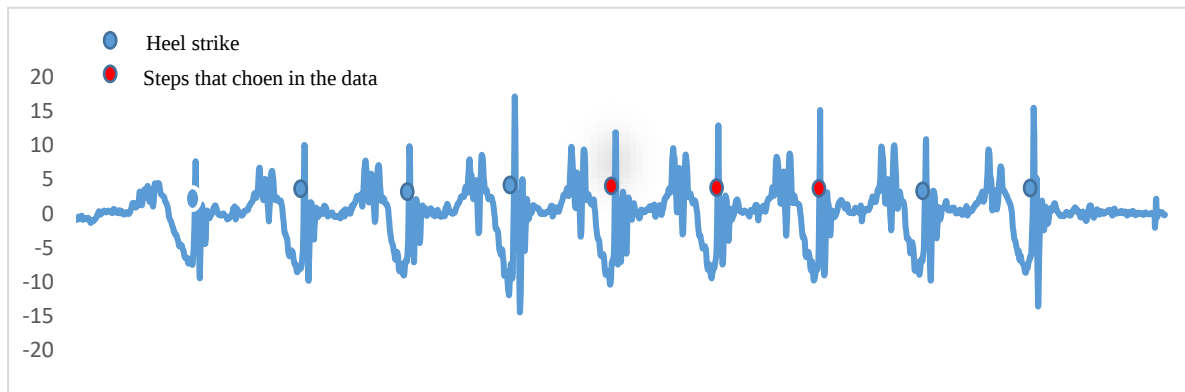


Fig.4. Heel strike start with the positive peaks acceleration from smartphone accelerometer

To assess the validity between the insole sensors and smartphones for each trial, the Pearson correlation was also used in this analysis. We used the following value to check the agreement between the device results: .90 to 1.00 as very high, 0.70 to 0.90 as high, and 0.50 to 0.70 as moderate, 0.30 to 0.50 as low, and less than 0.30 as insignificant. These metrics and ranges have been used by a number of studies [17-19].

Based on Fig 4, it could be seen that the insole pattern in the forward and upward directions was more stable most of the time because it depends on the leg pressure sensor. However, with the smartphone, most of the patterns showed more stable steps in 5-7 because the accelerometer data depends on the walking action. In other words, walking speed differs at the beginning of walking and when preparing to stop. Moreover, the data of the smartphone accelerometer in the forward and upward directions showed some noise and negative signals in the pattern, although we used only the positive signals.

The change of sign of the positive peak in the acceleration signal in the anterior-posterior direction is taken as the instance of the foot contact [20]. In step time and stride time, the average of the time for the three middle steps (5-7) steps was calculated. In other words, in this paper, we added the time of three

steps and then divided it by 3, and the same for stride time but for three strides. The processing of cadence was carried out similar to [21] but we converted the time to seconds because the time of both devices (smartphone and insole sensor) was measured by seconds. To validate the accelerometer's ability to detect the number of steps, the subject walked 10 meters depending on the lap distance on a flat floor indoors.

III. EXPERIMENT RESULTS AND DISCUSSIONS

The purpose of this study was to compare and quantify the validity of spatiotemporal gait parameters between smartphone and insole sensors. For that purpose, in this paper, a series of experiments were conducted to evaluate the performance of the smartphone device to study the spatiotemporal parameters. In this test twenty participants: healthy young adults (10 males and 10 females; aged between 20 and 40 years; mass and height 60 to 95 kg and 156 to 180cm, respectively), were recruited and they successfully completed the testing in the laboratory environment. Different sets of parameters: step time, stride time, cadence and walking speed, were collected in this study. each subject completed 5 trials. Then, spatiotemporal gait parameters were collected and utilising two

smartphones and two insole shoes sensors. In the trials, the smartphone showed similar results when compared with those of the insole. The results of each subject (left and right) were reported in terms of mean and standard deviation (SD), as shown in Tables 1 and 2. These statistical measures have been used by many researchers to evaluate their methods [14, 22]. Results of all the experiments were analysed using SPSS. Tables I and II show the average (for 20 subjects) of four parameters for left and right insole sensor and smartphone, based on mean and SD.

smartphone has the ability to study the spatiotemporal parameters for healthy people.

To highlight more evaluation of the proposed study in term of the comparison between smartphones and insole sensors, the 25 trials were also used in this study to investigate the relationship between the insole and smartphone. The results for each subject is based on four parameters: step time, stride time, Cadence and walking time, and are reported in terms of mean $\pm$ standard and then the average of mean $\pm$ standard was calculated for all subjects, as shown in

TABLE I. The performance of the proposed method based on four parameters - left insole sensor and smartphone for five trials m/s

Variable	Insole		Smartphone	
	Mean	SD	Mean	SD
Step time	0.68	0.03	0.67	0.03
Stride time	1.22	0.06	1.22	0.06
Cadence	50.05	0.92	49.35	1.03
Walking time	1.03	0.05	1.02	0.05

TABLE II. The performance of the proposed method based on four parameters - right insole sensor and smartphone for five trials m/s

Variable	Insole		Smartphone	
	Mean	SD	Mean	SD
Step time	0.68	0.02	0.69	0.03
Stride time	1.21	0.05	1.21	0.05
Cadence	49.81	0.78	49.41	0.96
Walking time	1.01	0.05	1.01	0.05

The mean and SD for each subject based on the four parameters were computed. The average was calculated for each parameter for both insole sensors and smartphones. Based on the results in Tables I and II, the mean and SD for insole and smartphone based on four parameters yielded approximately the same results. The results demonstrated that the

Table III. The results for the smartphone demonstrate that the proposed study achieved better performance when comparing smartphone and insole sensors. Of the four parameters, the step time results performed best in term of average of mean and SD for all subject compared with other parameters. From Table III, one can see that the smartphone pair

TABLE III. The results for mean $\pm$ standard of 25 trials

Parameters	Insole		Smartphone	
	Right	Left	Right	Left
	mean $\pm$ standard	mean $\pm$ standard	mean $\pm$ standard	mean $\pm$ standard
Step time	0.76 $\pm$ 0.03	0.74 $\pm$ 0.03	0.78 $\pm$ 0.03	0.73 $\pm$ 0.03
Stride time	1.30 $\pm$ 0.05	1.31 $\pm$ 0.05	1.27 $\pm$ 0.24	1.31 $\pm$ 0.05
Cadence	45.41 $\pm$ 1.75	45.78 $\pm$ 1.62	45.75 $\pm$ 1.60	45.73 $\pm$ 1.74
Walking time	0.92 $\pm$ 0.09	0.89 $\pm$ 0.08	0.90 $\pm$ 0.06	0.89 $\pm$ 0.07

TABLE IV. Summary of result agreement between smartphones and insoles for two subjects with 25 trials

Variable	Right		Left	
	Pearson r	P-value	Pearson r	P-value
Step time	0.79	0.42	0.79	0.26
Stride time	0.92	0.31	0.88	0.08
Cadence	0.80	0.47	0.88	0.08
Walking time	0.82	0.46	0.80	0.94

achieved acceptable results compared with that of the insoles. The P-value was used to determine significance by presenting the agreement between the smartphones and insoles. The differences between the data derived from the insole sensor and smartphone were not-significant for all indicators (P-value >0.05), reflecting the similarity between these two devices, as shown in Table IV. Results confirm the hypotheses formulated prior to this study and therefore are supportive of increased adoption of smartphones for collecting spatiotemporal data instead of insole sensors.

Table 4 shows the summary of results based on the Pearson correlation coefficient (r) and P-value between the smartphones and insole sensors for all subjects with 25 trials. For (r) values 0.90-1.00 considered very high, 0.70-0.90 high, 0.50-0.70 moderate, 0.30-0.50 low and less than 0.30 considered negligible. The P-value was calculated

for all parameters through insole and smartphone (Left and right). The results in Table IV show that each parameter of insole and smartphone could be presented by a specific set of P-value.

A. Performance of the study based on Bland Altman plots

Bland Altman plots were used to assess this study's ability to investigate the effectiveness of the variables (step time, stride time, cadence, and walking speed). Bland Altman plots are another way to examine the agreement and systematic error between the smartphones and insoles [19]. The x-axis represents the average of the two systems' values while the y-axis represents the difference between the two values. The Bland Altman graph has three horizontal lines that provide more information about the acquired data. The solid line,

called the bias, represents the average differences between the two values and the two dashed lines represent the limit of agreement (LOA). Bland Altman plots provide bias and 95% limits of agreement when comparing the spatiotemporal gait parameters derived from the smartphones and insole sensors, as shown in Fig 5. If 95% of the values fall between the dashed lines, the difference is normally distributed [23]. Based on the obtained results in Fig 5, we can observe that there are no big differences in the obtained results when the smartphones and insole sensors were used, indicating that there is an agreement between both devices. From these results,

it is evident that the smartphone has the ability to determine spatiotemporal gait parameters, and to evaluate the validity of a smartphone-based tri-axial accelerometer to assess gait characteristics.

B. Performance of the proposed study based on 25-cross validation

To investigate the effectiveness of the smartphones as opposed to the insole sensors in determining spatiotemporal gait parameters (step time, stride time, cadence, and walking speed), box plots were used based on the Pearson correlation coefficient. The box plots consist of three parts: upper, lower,

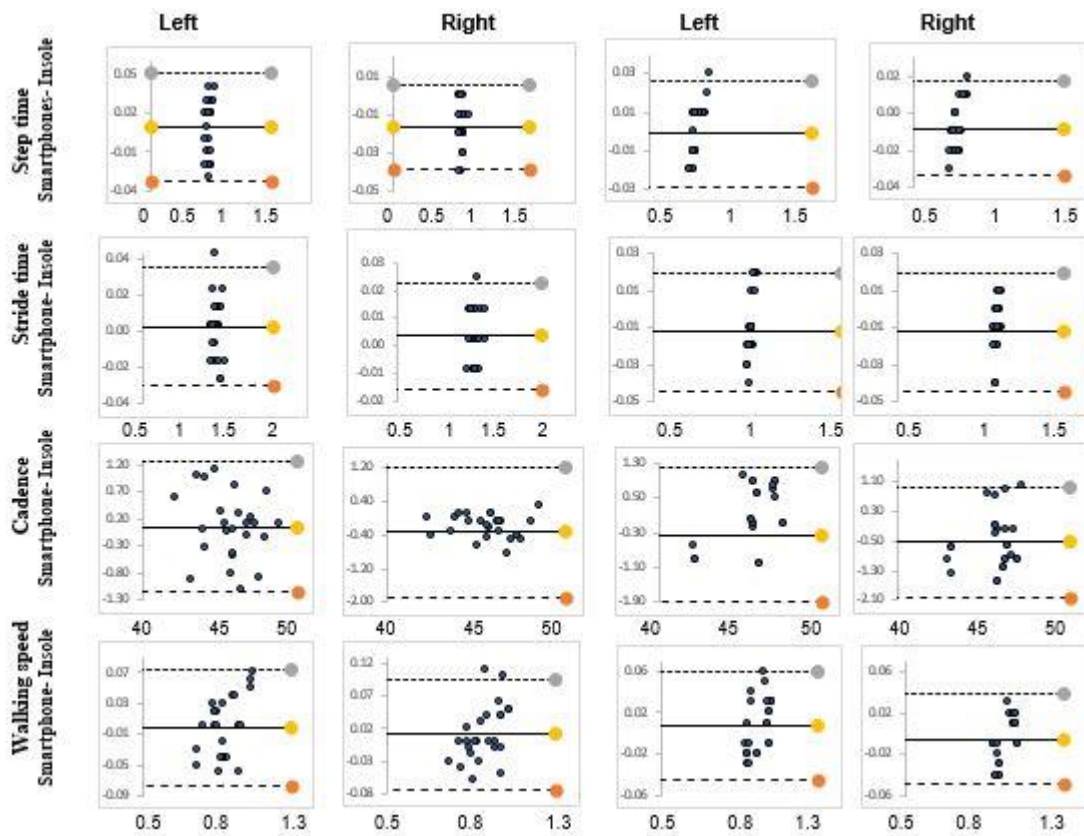


Fig. 5. Bland-Altman plot for the Samsung smartphone attached to subject body and insole sensors for two subjects with 25 trials. Each dot represents a single step. The solid line is the bias, with dashed lines representing the upper and lower of error LOA

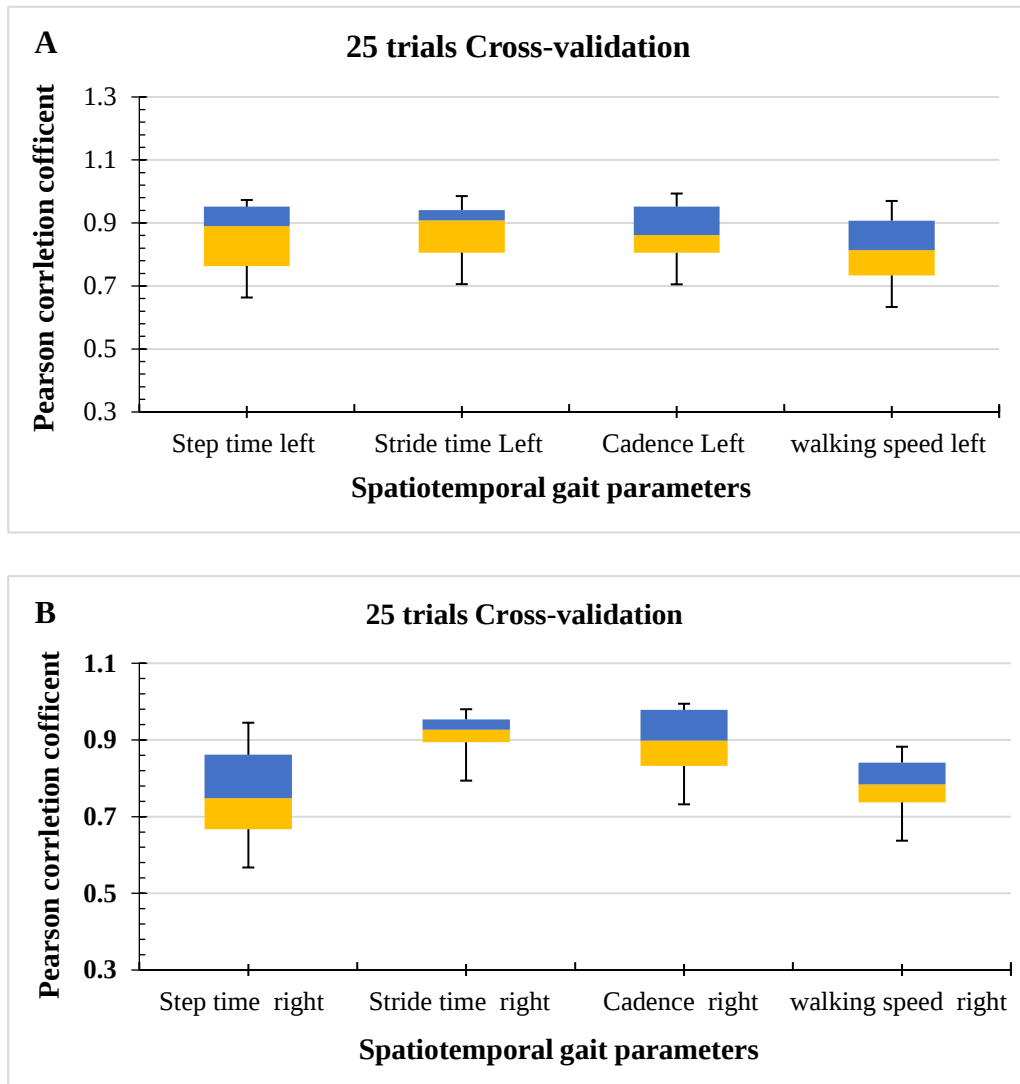


Fig. 6. Box plot for Pearson correlation coefficient of smartphones and insole sensors: A present the left leg and B show the right leg

and middle Figs 6. The upper part of the plot box denotes the 75th percentile, and the lower part presents the 25th percentile, while the central part refers to the median 50th percentile which is sometimes called the centre. The highest and lowest values in the box plot are marked using a line extending from the top to the bottom of the box. The box plot shows agreement between smartphones and insole sensors at the same time point based on the Pearson correlation coefficient. In further investigations, the performance of the proposed

method through 25- cross validation using smartphone device was used in this study. The proposed method was tested 25 times and all the results were recorded. From Figs 6 a and b we can see that Pearson correlation coefficient ranged between 0.79 and 0.92 for left and right. In the results in Fig 6 a, the value of the maximum Pearson correlation coefficient was 0.98% for stride time left, while the minimum value was 0.68% for walking speed left. On the other hand, the maximum and minimum Pearson correlation coefficient for the

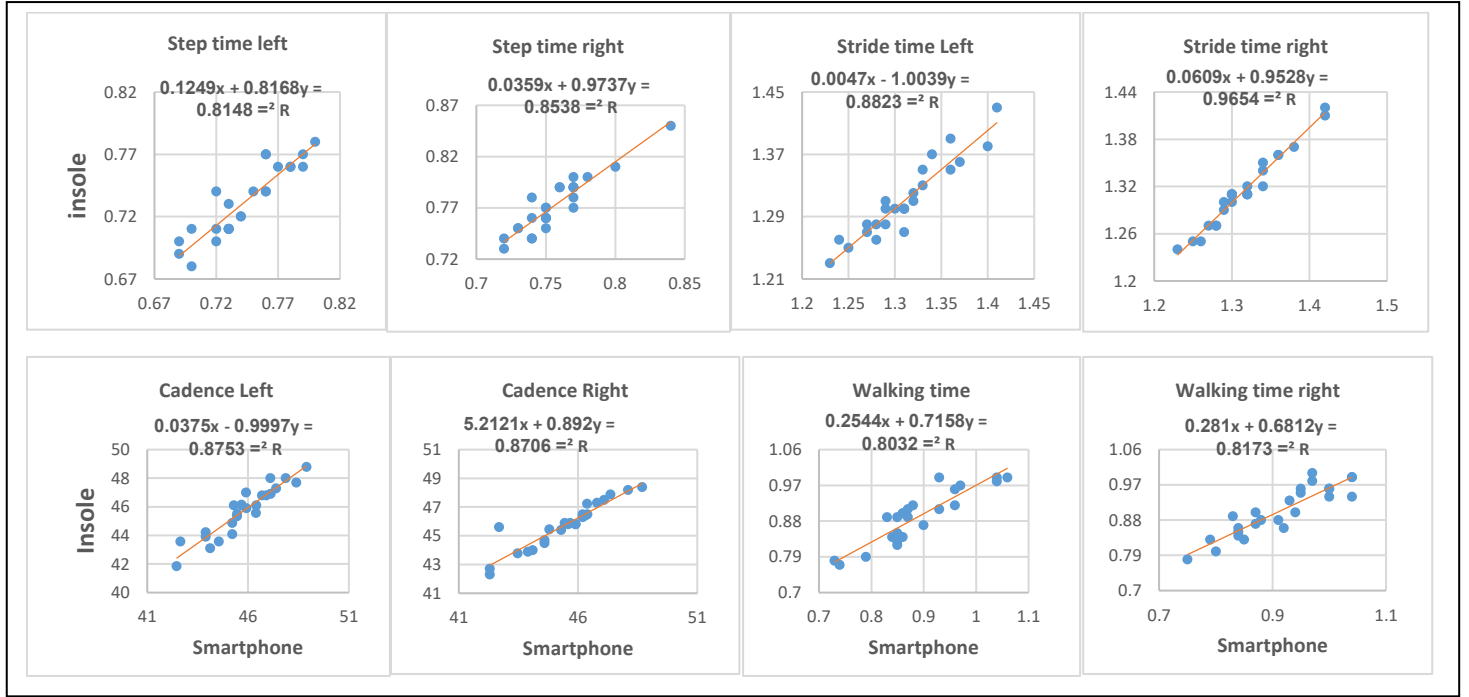


Fig. 7. shows the scatterplot of the smartphone device (G^{sd}) vs Insole sensor (G^{se}) for the left and right legs.

right limb was 0.98% and 0.65% for stride time and step time, respectively. These results support the research findings summarised in

For further evaluation of the study, the behaviours of the smartphones and insole sensors were analysed and tested for spatiotemporal gait parameters using R-squared (R^2). Fig 7 shows the scatterplot of the insole sensor (G^{se}) vs smartphone device (G^{sd}) with the least square regression, line, $[y (G^{sd}) = aG^{se} + b]$, and correlation of determination (R^2) which is used to evaluate as well as to show the agreement between smartphones G^{sd} and insole sensors G^{se} for all gait parameters. The constant values of a and y -intercept b were used outline the model's performance, with the correlation of determination (R^2), was employed. Reliable results were found for all four parameters: step time, stride time, cadence and walking, based on the value a , b and R^2 . Furthermore, it was noticed that there is agreement between the smartphones and insole sensors, which

reported the same or similar results. The results for the left leg were $R^2 = 0.81\%$, 0.88% , 0.87% and 0.80% for step time, stride time, cadence and walking, respectively, while results for the right leg were $R^2 = 0.85\%$, 0.96% , 0.87% and 0.81% for step time, stride time, cadence and walking, respectively. Finally, the experimental outcomes indicate that the proposed method is capable to study the spatiotemporal parameters of healthy people: step time, stride time, cadence, and walking speed, using both insole sensors and smartphones.

Regarding the validation study, [15] proposed the same method of validation as our study; a smartphone device used to compare the motion capture systems. In their study, 22 healthy young adults were assessed with a smartphone application and a motion capture system. The reliability of the proposed method was evaluated using the correlation coefficient and standard error. The validity of the smartphone application and motion capture-derived values were compared with the Pearson correlation coefficient and Bland-Altman

limits of agreement. They demonstrated that there was agreement in the obtained results of the systems. Another study was presented by [24] in which the reliability and validity of a smartphone-based accelerometer in quantifying spatiotemporal gait parameters of stroke patients when attached to the body were confirmed. In their study, the gait parameters were measured and evaluated using a smartphone accelerometer and GAITRite analysis.

Thirty participants were asked to walk 10 meters. Then three parameters: gait velocity, cadence, and step length were computed using smartphone-based accelerometers. The results were validated with a GAITRite analysis system. Average excellent reliability (ICC2, $1 \geq .98$) of correlation coefficient was reported. They observed that the high correlation between the smartphone-based gait parameters and GAITRite analysis system-based gait parameters was achieved.

Following [25], we used step time, stride time, cadence, and walking speed for a comparison of spatiotemporal gait parameters between smartphone and insole sensors. Furthermore, the Bland-Altman 95% bias and limits of agreement, linear regression and statistical analysis using mean and standard deviation were also employed to evaluate the obtained measures and to assess the agreement between the two systems. The comparison between the devices showed excellent agreement. In summary, from all the obtained results above, we can notice that specific opportunities exist for smartphone-based gait assessment as an alternative to conventional gait assessment. Furthermore, a smartphone-based gait assessment could provide reliable information about changes in the spatiotemporal gait parameters.

CONCLUSION

The characteristics of a smartphone application were used to study the spatiotemporal parameters: step time, stride time, cadence and walking speed of both insole sensors and smartphones for healthy people. In this work, an innovative method was used to extract the most important features from 20 subjects. One of the most important findings was that the measures of the smartphone device agree with the insole shoe sensors when measuring spatiotemporal parameters. The effectiveness of the proposed model was tested with two Android smartphones and 20 healthy adult participants. The study used different statistical methods (ANOVA, Bland-Altman, linear regression, and Pearson correlation coefficient) to measure the reliability and validity of smartphone use. Smartphone use was also compared with four other existing methods. It was demonstrated that the developed model achieved the best performance in terms of a correlation coefficient.

The obtained results showed that, by using two Android smartphone devices with Insole shoe sensors, a high level of agreement was obtained, allowing for a good range of acceptable alternatives to assess spatiotemporal parameters. Our findings also demonstrated that the smartphone can be used as a reliable and valid tool in spatiotemporal gait analysis of healthy adults. This method can help a clinician to work more efficiently and to objectively evaluate gait with easy to use and interesting work as well as to reduce cost. In the future, additional studies will be needed to investigate the ability of smartphones to detect the differences between adult and older people in their way of walking and to ascertain whether it is sensitive enough to detect differences in gait patterns. Furthermore, we can apply big data and different devices to study the spatiotemporal parameters of the insole sensors and smartphones for healthy and non-healthy people.

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