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Examining Gait Characteristics in People with Osteoporosis Utilizing a Non-Wheeled Smart Walker through Spatiotemporal Analysis

Nazia Ejaz [1,2], Saad Jawaid Khan [3,*], Fahad Azim [1], Mehwish Faiz [3], Emil Teuțan [4], Alin Pleșa [4], Alexandru Ianosi-Andreeva-Dimitrova [4] and Sergiu-Dan Stan [4,*]

1 Department of Electrical Engineering, Ziauddin University, Karachi 74600, Pakistan; nazia_ejaz94@yahoo.com (N.E.); fahad.azim@zu.edu.pk (F.A.)
2 Department of Biomedical Engineering, Balochistan University of Engineering & Technology, Khuzdar 89100, Pakistan
3 Department of Biomedical Engineering, Ziauddin University, Karachi 74600, Pakistan; mehwish.faiz@zu.edu.pk
4 Department of Mechatronics and Machine Dynamics, Technical University of Cluj-Napoca, 400114 Cluj-Napoca, Romania; emil.teutan@mdm.utcluj.ro (E.T.); alin.plesa@mdm.utcluj.ro (A.P.); alexandru.ianosi@mdm.utcluj.ro (A.I.-A.-D.)
* Correspondence: sj.khan@zu.edu.pk (S.J.K.); sergiu.stan@mdm.utcluj.ro (S.-D.S.)

Abstract: Fragility fractures, caused by low-energy trauma, are a significant global health concern, with 158 million people aged 50 and over at risk. Hip fractures, a common issue in elderly patients, are often linked to underlying conditions such as osteoporosis. This study proposed a cost-effective solution using a non-wheeled smart walker with load sensors to measure gait parameters, addressing the high cost of traditional gait analysis equipment, the prototype used PASCO load cells PS2200 for force measurement, eliminating the need for Arduino UNO or microcontroller-based hardware. A lightweight amplifier PS2198 amplified the signal, which was transmitted via USB to a personal computer. PASCO capstone software was used for data recording and visualization. The smart walker was tested on forty volunteers divided into two equal groups: those with osteoporosis and those without, by performing a 10 m walk test three times. ANOVA comparing spatiotemporal parameters (TSPs) of the two participant groups ($\alpha = 0.05$) showed that significant differences lay in terms of time taken to complete the walk test ($p < 0.01$), left step length ($p = 0.03$), walking speed ($p = 0.02$), and stride length ($p < 0.02$). The results indicate that this smart walker is a reliable tool for assessing gait patterns in individuals with osteoporosis. The proposed system can be an alternative for time consuming and costly methods such as motion capture, and for socially stigmatizing devices such as exoskeletons. It can also be used further to identify risk factors of osteoporosis.

Keywords: fracture prevention; bone health; mobility aid geriatric care; spatiotemporal analysis; osteoporotic fractures; hip fracture; elderly healthcare; biomechanical assessment; fall prevention; osteoporosis management; physical therapy; musculoskeletal disorders; aging population; medical technology; clinical research; bone density; patient rehabilitation; functional mobility; osteoporosis diagnosis

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1. Introduction

Osteoporosis is a medical condition distinguished by a reduction in bone mineral density. It can be coupled with a decline in muscle mass and an increase in the deposition of adipose tissue. These physiological alterations can influence an individual's gait and equilibrium, increasing their vulnerability to falls and fractures [1]. The decrease in bone density in osteoporosis causes injury to the hip joint by exposing it to heightened stress levels. This phenomenon is notably prevalent in postmenopausal females. The increased stress makes seemingly healthy hip joints susceptible to osteoarthritis through perturbations to the typical patterns of gait and balance [2].

While conventional methods for assessing gait disturbances and fear of falling in persons with bone diseases exist, they often necessitate manual patient evaluations, which can be cumbersome for both the patient and the clinician. For instance, the dual cognitive task test can gauge gait abnormalities in individuals afflicted with osteoporosis and a fear of falling [3], while the ten-meter test assesses the impact of training programs on balance, gait velocity, and muscle strength in people with osteoporosis [4]. However, these manual assessments mandate specialized testing facilities and trained therapists to administer them, rendering them impractical in various settings.

To address these challenges, alternative automated systems have emerged to conduct gait analysis and assessments [5]. These systems encompass a wide array of technologies, including motion capture systems [6,7], and video cameras [8]. While undeniably effective in suitable contexts with the requisite infrastructure and trained personnel, these methods are not universally accessible or convenient.

Another avenue involves the utilization of sensors, such as inertial measurement units (IMUs) [9], wearable sensors [10], or insole foot pressure sensors and accelerometers [11,12]. These sensors offer the advantage of portability and can be employed in diverse environments. However, they necessitate attachment to specific body locations, which may not always be convenient or comfortable for the user.

A promising solution to these challenges lies in the integration of gait-monitoring sensors into mobility aids commonly used by individuals, such as rollators [13–15], and canes [16,17]. This innovative approach ensures that gait analysis is accessible irrespective of location or time, without requiring specific body attachments. Nonetheless, it is essential to note that this method may yield approximated gait information and, consequently, is susceptible to a margin of error compared to more intricate systems [18].

Moreover, the current focus primarily gravitates towards rollators, often equipped with wheel encoders to estimate the distance covered. However, an often-overlooked segment of the population consists of users with pronounced instability, rendering rollators impractical and even hazardous during routine activities or gait monitoring. Consequently, non-wheeled walkers emerge as a pertinent alternative in facilitating gait analysis for individuals grappling with high instability and an aversion to the risks associated with traditional rollators.

Numerous studies have been conducted to analyze gait through different techniques. The four common techniques including the use of a cane, robotic walker, pick up standard walker, and smart walker/rollator are presented in Table 1.

Table 1. Related work based on robotic walkers, canes, wheeled walkers, and standard walkers.

Robotic Walkers					
Reference	**Technology**	**Methods**	**Results**	**Limitation**	**Year**
[19]	Mobility Assistance Robotic rollator	Data was collected by using a Laser range finder	Detected gait phases	Users needed to wear fitted clothes	2014
[20]	Assistive Robot	A proximity Sensor was used by a robotic walker to measure the distance between the user's leg and the robot.	Controlled forward walking speed of the robot according to distance between the user and robot.	Only distance and walking speed were detected.	2018
[21]	Robotic Walker; Walk-IT	Multi-camera and multimodal dataset was used for biomechanical analysis.	Biomechanical analysis of posture and gait, pose estimation, and human gait detection and tracking algorithm.	Need to wear full body motion tracking system.	2022

Table 1. *Cont.*

Canes					
Reference	**Technology**	**Methods**	**Results**	**Limitation**	**Year**
[16]	Cane	A Force sensor was attached to measure the load on the cane.	Continuously measurement using weight bearing during walking	No temporal-spatial gait parameters were estimated in this study.	2019
[22]	Cane Robot	Laser range finders were used to detect the user's leg motion.	Spatiotemporal gait parameters were measured	Users needed to wear tight pants or short skirts during monitoring.	2022
Wheeled Walkers					
Reference	**Technology**	**Method**	**Results**	**Limitation**	**Year**
[14]	i-Walker Platform	Force sensors were embedded on handlebars of the walker.	Extracted spatiotemporal gait parameters.	The user needed to put a mass of at least 3 kg on the walker handlebars for use	2015
[23]	Smart Walker	Gait monitoring by using feet position and orientation by using ISIR's smart walker prototype with Active depth sensor.	Spatial patterns are reported in this study by using a camera depth sensor without markers.	Spatiotemporal parameters were not reported in this study.	2015
[24]	Wheeled Walker	Microwave Doppler radars are embedded in the four wheels of the walker.	Gait velocity estimation for normal and abnormal gait.	Important gait parameters for diagnosis of the user's condition are not the scope of this study for instance cadence, step length, etc.	2015
[18]	i-Walker Platform	Embedded force sensors in handlebars of the walker.	Estimated force difference of handlebar sensors during walking	This system was interfaced with the optotrack system and a treadmill, so it needed a confined environment for operation.	2016
[25]	Smart Rollator, i-Walker	Data of volunteers using a smart rollator based on a force sensor, an accelerometer, and a gyroscope was classified using machine learning.	Found distinct walking-age groups according to walking speed, the forces exerted by the individual on the i-Walker.	For assessment only two parameters were known i.e., walking speed and force.	2018
[26]	Smart Walker	Smart Walker based on functionalities sit-stand assistance, navigation system, and obstacle detection with gait monitoring.	The gait parameters determined by smart walker and GaitRite were concurrently validated.	This walker only determined temporal gait parameters and extraction of spatial gait parameters are not in the scope of this system.	2019
[27]	Smart Rollator Walk-IT	Open-source modular-based rollator for gait monitoring and support. It included force sensors, encoders in the wheel, and light detection and ranging sensors.	Assessment of spatiotemporal gait parameters by leg speed information and weight bearing of users.	The main draw of this device was that it needed users' leg visibility during rollator use due to a laser-based gait analysis system. Walk-IT also encountered visibility issues when it came to tracking steps, a crucial element for gait assessment.	2022

Table 1. *Cont.*

Standard Walker					
Reference	**Technology**	**Method**	**Results**	**Limitation**	**Year**
[28]	Pick up standard walker	In this study force sensors, light detection and ranging sensors were embedded in the walker's legs.	Force unbalance on the walker's leg and motor incoordination was estimated.	Spatiotemporal gait parameters were not in the scope of this study.	2018

While assessing rehabilitative devices and identifying functional limits resulting from pathologies, three-dimensional instrumented gait analysis is a useful technique. Typical components of gait analysis include analysis of spatiotemporal parameters, joint kinetics (moments and power), kinematics (joint angles and ranges of motion), and ground reaction force analysis [29]. Research in gait analysis has been limited by focusing on specific parameters such as walking speed, and spatiotemporal parameters [23,25,26]. These parameters provide valuable insights into individual gait pattern s [30] but only represent a portion of the multifaceted domain. Walkers have been used to measure temporal, and spatial parameters [26], but often interconnected with other systems like GaitRite or treadmills, limiting their applicability to controlled environments. Alternative solutions such as the cane robot [22], Robotic walker Walk-IT [21], and smart rollator walker [19] have been employed to assess gait parameters, but they impose certain prerequisites on participants, such as wearing tight-fitting clothing or short skirts for enhanced leg movement visibility. Other devices such as the JARoW [31], i-Walker [32], and FriWalk robotic walker [33] have also been proposed and offer a good range of sensory and motor applications [34]. However, these devices are either too expensive for a developing country end-user or are too complicated to be operated by the user without the help of a specialist.

In response to these limitations, the present study endeavors to fill the gap by introducing a smart walker specifically designed to facilitate a detailed gait analysis. The smart walker allows for analysis of spatiotemporal gait parameters and offers users valuable support while minimizing the risk of fall-related injuries, a concern often associated with traditional wheeled walkers. The design of the walker places minimal weight-bearing demands on the user, making it suitable for individuals with walking disabilities undergoing rehabilitation treatment using standard walkers.

To assess the device's effectiveness, we conducted a pilot study involving 40 participants in an urban setting. The study included a detailed gait analysis of differences between individuals with and without osteoporosis to validate the proposed smart walkers' utility in people with osteoporosis. Our findings show that the benefits of the smart walker extend beyond its functional capabilities. The lack of specific attire during gait monitoring promotes greater convenience and ease of use. Specific infrastructure, such as treadmills or video cameras, is not required for its operation. This makes it suitable for a wide range of clinical and healthcare settings, including rehabilitation centers, homes, and outdoor environments.

Notably, the versatility of this developed smart walker extends beyond its functional capabilities; it does not depend on any specific infrastructure, such as treadmills or video cameras, for its operation. This feature significantly enhances its suitability for a wide range of clinical and healthcare settings, including rehabilitation centers, homes, and outdoor environments, effectively eliminating the need for participants to wear specific attire during gait monitoring, thereby promoting greater convenience and ease of use.

2. Materials and Methods

A smart walker prototype was designed to facilitate the monitoring of gait patterns in people with osteoporosis during the rehabilitation process. The prototype featured onboard force sensors integrated into the walking aid. These sensors enabled the acquisition of spatiotemporal gait parameters, including walking speed, cadence, step length, step time, stride time, and stride length. The prototype's design aimed to obviate the need for participants to wear external sensors or rely on specialized equipment such as treadmills, electronic walkways, or post-processing-dependent video cameras.

The prototype was tested on 40 volunteers, comprising 20 healthy elderly individuals and 20 older individuals diagnosed with osteoporosis. The study design was quasi-experimental, where a physiotherapist administered a standardized 10 m walk test, systematically. Spatiotemporal parameters were acquired through the smart walker including the time of walk, walking speed, cadence, step length, step time, stride time, and stride length.

Figure 1 shows Smart Walker prototype equipped with PS2200 Force Sensors. In total, four force sensors were attached on walkers legs including Force sensor on rear right side (**Fs***RRs*),Force Sensor on rear left side (**Fs***RLs*), Force Sensor on front left side (**Fs***FLs*), and Force Sensor on front right side (**Fs***FRs*).The developed prototype smart walker with the positions of sensors and electronic components labelled, walker with on board sensors, providing a visual representation of the device that was used to collect data in this study. A walker made up of aluminum body and soft rubber pads on the handlebars was utilized to assist people with osteoporosis in maintaining gait balance, stability and support during their rehabilitation process. We equipped this commercially available walker with four sensors, which were placed at the front and rear legs of the walker to measure the upper limb forces during walking. The sensors were embedded at a distance of 0.7112 m (28 inches) away from the handgrips to avoid damage from overloading. PASCO load cells PS2200 were used as a sensor in this prototype, which measured forces in all directions, eliminating the need for Arduino UNO or microcontroller-based hardware for data transmission. A lightweight load cell amplifier PS2198 was used to amplify the sensor signal, which was then transmitted to a personal computer via USB interface. The sensor signal amplifier PS2198 and USB interface PS2100 are light weight and easily travel with handheld data loggers. For data recording and visualization, PASCO capstone software v 2.0 (free trial) was used, displaying a graph of forces of right and left hands on the handlebars of walkers versus time of the walk. The system is wired but this cannot affect the measurements due to the Well-fitted sockets (six-pin mini-DIN jacks) of amplifier and USB interface which connects walker sensors to personal computer for data recording. Due to wired connections, the current design allowed users to walk up to 15 m. To record gait daily or weekly the user at home needs to setup the hardware and software as follows:

Hardware setup:

i. Connect four separate load cells to the input ports of the amplifier.
ii. Connect the cable of the load cell amplifier to a PASPORT interface.
iii. Connect the PASPORT interface to Personal Computer USB port.

Software setup (Data studio):

i. Once you connect the load cell amplifier to the computer via a PASPORT interface, the PASPortal window will open automatically as shown in Figure 2.
ii. Select launch Data Studio in PASPortal window.
iii. Click 

to begin data collection.

Users can save recorded data and can share it with therapist electronically for gait assessment. After recording data, the user can disconnect the amplifier and USB interface from sensor to use walker for gait support and rehabilitation every time and everywhere.

The software setup image shown in Figure 2 is taken from https://www.conatex.be/media/manuals/BAEN/BLEN_1091161.pdf source (accessed on 1 October 2023).

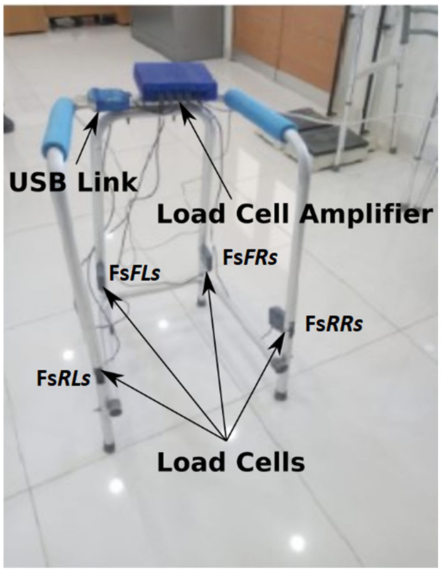


Figure 1. Smart Walker with on board sensors.

Figure 2. PASPortal window, software operation during data collection.

2.1. Sensor Specifications and Calibration

The ranges of force sensors PS2200 used in this study are 100 ± 5 N with safe overloads of up to ±150 N. The average sampling rate in our recorded data is 20 Hz, the sensor has taken a new sample after every 0.05 s. The maximum sampling rate of sensor can be increased up to 500 Hz. The accuracy of sensor signal amplifier is ± 1 N, and a resolution of 0.003 N. We calibrated force sensors to ensure the accuracy and consistency of data recording. Calibration of force sensors were performed by hanging standard weights of 1 kg, 2 kg, 3 kg, and 4 kg on middle of handlebars of walker on right and left side. The hanging weight was distributed in rear and front sensor. By using Equations (1) and (2), the weight distributed on the rear and front sensors were summed which was approximately same to the standard weights hung on the handlebars of the walker. FL in Equation (1) shows total force on left handlebar and in Equation (2) FR shows total force on right handlebar of walker. The accuracy of the sensors was presented in Figure 3. The percentage error of the left force sensors was 1.36% and of the right force sensors were 1.18%.

$$\mathrm{FL} = \mathbf{Fs}RLs + \mathbf{Fs}FLs \tag{1}$$

$$\mathrm{FR} = \mathbf{Fs}RRs + \mathbf{Fs}FRs \tag{2}$$

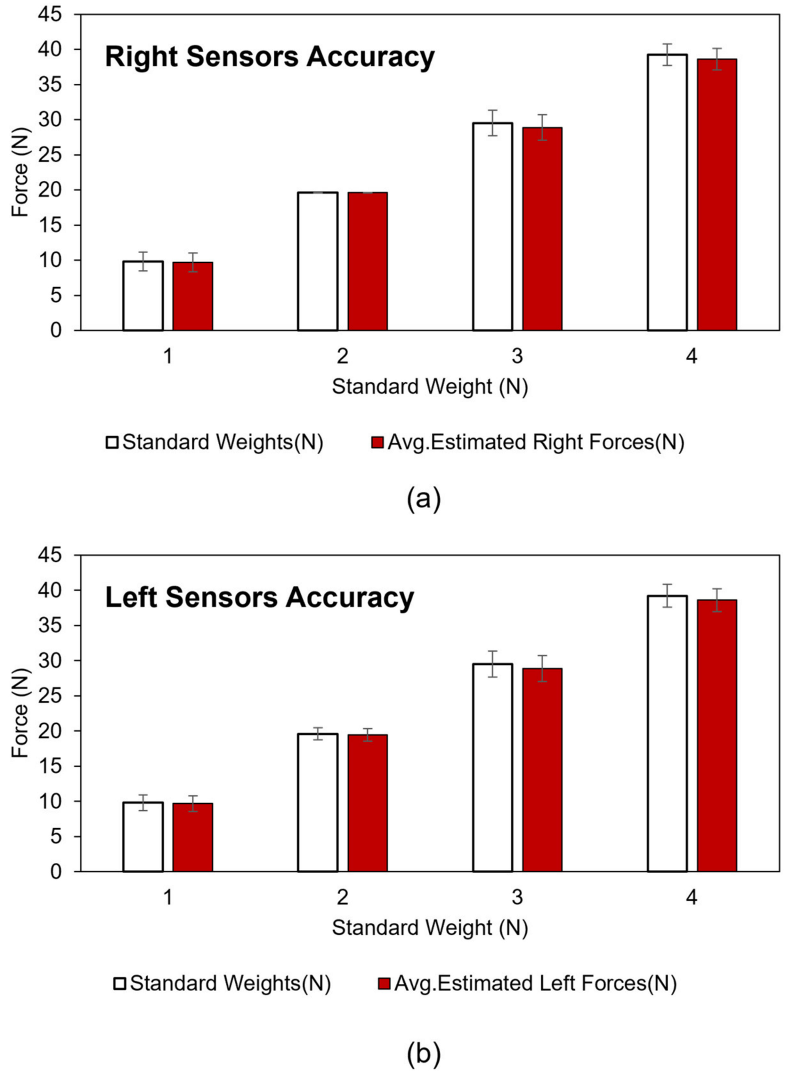


Figure 3. Validation of sensor measurement after calibration. (**a**) The sensor on the right handlebar, and (**b**) the sensor on the left handlebar.

2.2. Gait Parameters Estimation from Smart Walker with Onboard Sensors

The participant's weight distribution during walking was measured using the prototype Smart Walker. Figure 4 shows both left- and right-side forces recording from the four sensors with respect to time. Since the walker was easy to use for both groups of participants, and osteoporosis participants have experience in walker usage; thus, the data received have no significant errors and missing values. Therefore, no filters were used for data preprocessing before data analysis. The participants initiated walks by striking their right heel to the ground. At each heel strike we obtain the peak of force. The fluctuations in forces gave valuable information for the calculation of spatiotemporal gait parameters including time, stride time, stride length, cadence, step length, step time, and velocity. The force on the handlebar increased on the same side and lowered on the opposing side when users initiated a heel strike [14]. Hence, the number of steps taken by the users were easily determined by counting the number of inflection points as shown in Figure 4.

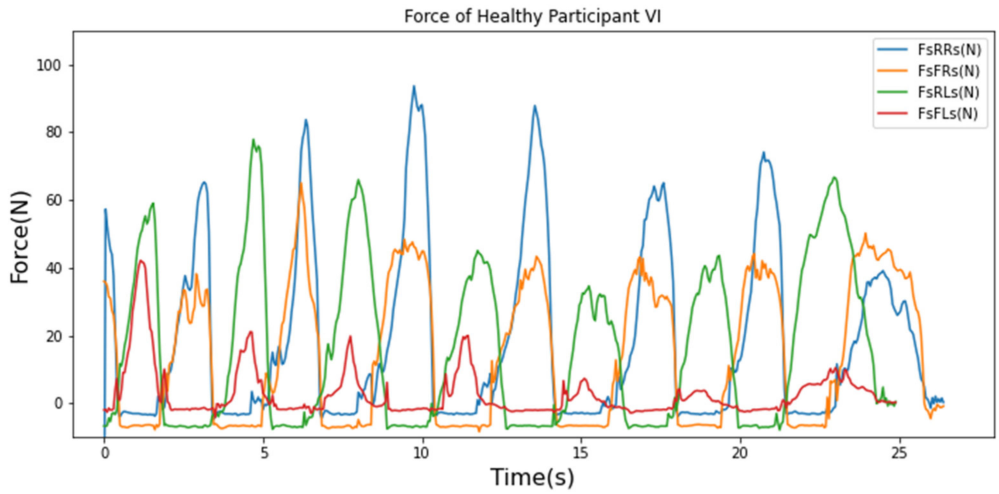


Figure 4. Force sensor reading. Force sensor on rear right side (FsRRs (N)), force sensor on rear left side (FsRLs (N)), force sensor on front right side (FsFRs (N)), and force sensor on front left side (FsFLs (N)).

For simplified data visualization, forces of two sensors attached on the left side (FsRLs + FsFLs) were added and resulted in a single force peak signal for the left heel strike, presented as the FLeft heel strike peak in Figure 5. Similarly, force measurements from the two sensors on the right side (FsRRs + FsFRs) were added to obtain one force peak signal, presented as the Fright heel strike peak in Figure 5.

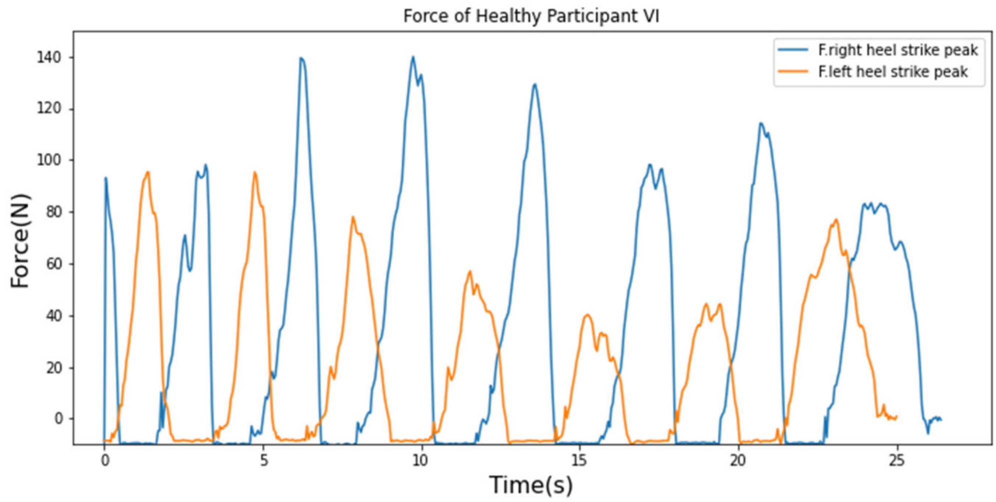


Figure 5. Sum of forces measured by sensor on rear and front (left) and on rear and front (right) during walk test using smart walker.

The differences in the forces recorded from left and right sides, occurrence of peaks at specific time and distance covered by the user, the following gait parameters were measured:

$$F_{diff} = F_{right\ heel\ strike\ peak} - F_{left\ heel\ strike\ peak} \tag{3}$$

Moreover, the following parameters were also measured:

Step Time: Average time in seconds between minimum–maximum (right) and minimum–maximum (left).

Stride Time: Average time in seconds between maximum–maximum (right) and minimum–minimum (left).

Number of steps: Number of inflection points.

Time required to complete walk: Number of seconds that a user takes to complete the walk.

Cadence: Number of steps taken * 60/time required to complete the walk.
Distance: The distance covered by user during test i.e., 10 m.
Walking Speed: Walking speed can be found by using distance (m)/time required to cover marked distance(s).
Stride length: Walking speed (m/s) * Average time in seconds between maximum–maximum (right) and minimum–minimum (left).
Step Length: walking speed (m/s) * Average time in seconds between minimum–maximum (right) and minimum–maximum (left).

$$User\ Support = F_{right\ heel\ strike\ peak} + F_{left\ heel\ strike\ peak} \quad (4)$$

After aggregating the forces exerted on the walker by the left and right sides for all walking steps, we determined the level of support provided by the user for propulsion. Equation (4) was used to calculate the amount of user support, with higher values indicating that the participant relied heavily on the walker for propulsion due to weak bone and muscle strength, resulting in high gait instability and balance issues. Conversely, lower values of user support indicated participants with better gait stability and balance who did not heavily rely on the walker for propulsion. Therefore, higher values of forces during walking were associated with gait abnormalities such as gait instability and balance issues.

2.3. Study Participants

Forty participants were recruited from The Ziauddin Hospital's Physical Therapy and Rehabilitation Centre in Karachi, Pakistan, as well as from three old age homes within Karachi, namely Anmol Zindagi, Gill Shelter Home, and Agosha-e-Afiyat. We studied 20 people with osteoporosis and 20 people without osteoporosis. In the group with osteoporosis, there were 6 males and 14 females, with a mean age of 70.85 ± 10.18 years. In the comparison group without osteoporosis, there were 11 males and 9 females with an average age of 69.85 ± 10.17 years.

The inclusion criteria for people with and without osteoporosis included being aged between 50 and 90 years old with the ability to use a walker. The group with osteoporosis included people with osteoporosis who were undergoing gait retraining using a standard walker as a rehabilitative aid and who were able to walk with a standard walker to perform their daily living activities. Exclusion criteria included individuals who had cerebral, neurological, cardiovascular or vision disorders other than osteoporosis, or individuals with osteoporosis plus othe disorders like stroke, ataxia, etc. We also excluded people who had a medical condition that affected their gait.

Ethical Approval

The Ziauddin university ethical approval policies for research conduct were followed, and informed consent was acquired from all participants.

2.4. Smart Walker Testing and Data Recording

All participants performed three walk tests at a distance of 10 m (10 m walk test) using the smart walker in the rehabilitation center, at the Ziauddin University Faculty of Physical Therapy under the supervision of a physical therapist and a nurse, as shown in Figure 6. A rehabilitation room with a plain smooth tiled floor was selected, and the volunteers were asked to walk using the smart walker on a smooth floor with shoes soaked with ink to produce marks on the floor. The participants were instructed to walk along a designated pathway while a therapist recorded the time using a stopwatch. In addition, step lengths (both right and left) and stride length were measured using a measuring tape. The walk test was used as a benchmark to validate our proposed system.

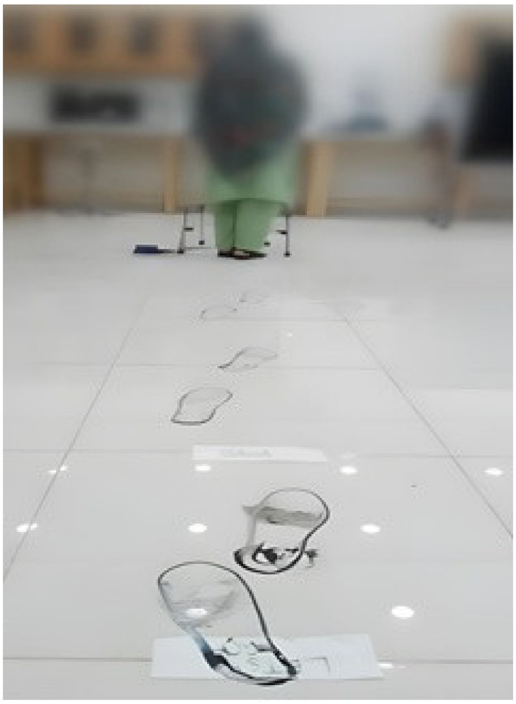


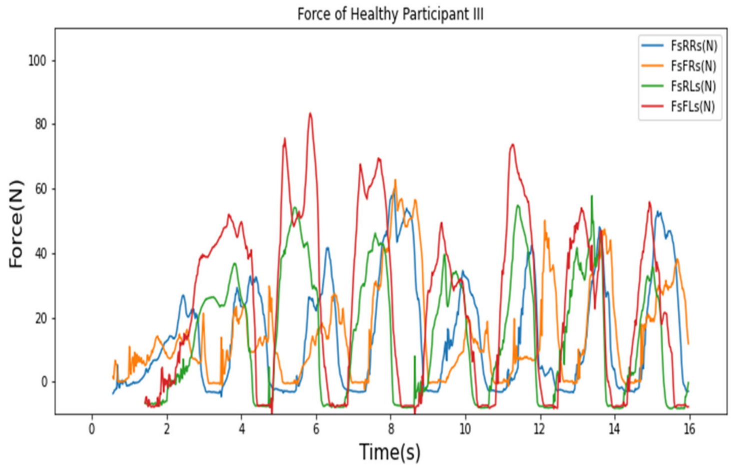
Figure 6. A 55-year-old female volunteer from the osteoporosis group performing a walk test.

3. Results

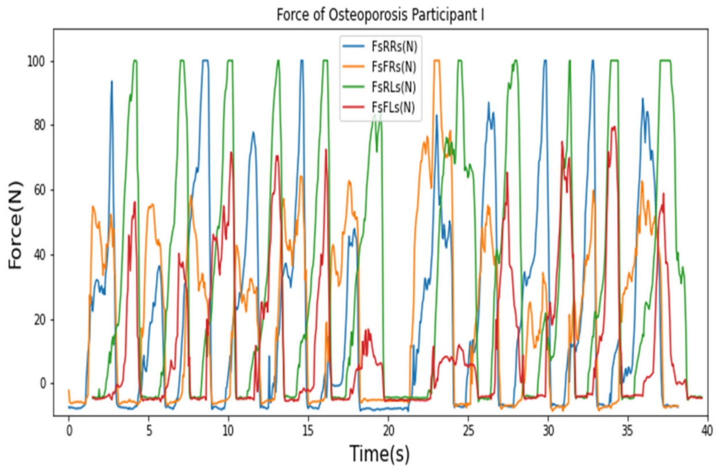
We conducted a 10 m walk test on the study participants using the smart walker to study gait patterns and associated forces exerted on the walker's handlebars during ambulation. The results showed significant differences in participants' gait dynamics. Specifically, as the participants initiated heel contact with the ground during their stride, discernible changes in the forces applied to the walker's handlebars were observed. This phenomenon was particularly evident when the participants made contact with their right heel, which correspondingly led to an augmentation in the forces registered on the right side of the walker's legs. Simultaneously, a reciprocal reduction in force was documented on the opposite side of the walker as illustrated in Figure 7.

Our analysis revealed that the inflection points in the force profiles corresponded to the instances of heel strikes during the participants' gait. This analysis allowed us to discern not only the number of heel strikes, but also the sequence in which they occurred. Evidently, the first heel strike typically originated from the right foot, marking the commencement of the gait cycle. The observation and quantification of these inflection points and heel strikes provided us with a precise and quantifiable measure of the number of steps taken by each participant during the 10 m walk test.

Figure 7 shows the generated graphs in Pasco Capstone software for the sensor recording on the walker, which measured the forces exerted by the upper limbs on the handlebars of the walker during walking. The graphical data was exported to an MS Excel file for the extraction of gait parameters. Analysis of the data revealed that users with osteoporosis exerted more force on the walker for propulsion compared to healthy users, as seen in Figure 7. Specifically, in Figure 7b, people with osteoporosis put over 100 N of body weight on the walker, while in Figure 7a, people without osteoporosis placed less than 100 N of their body weight on the walker.



(a)



(b)

Figure 7. Force sensor readings at every heel strike during the 10 m walk test. (**a**) People without osteoporosis, (**b**) people with osteoporosis.

The one-way analysis of variance (ANOVA) or F test was performed in order to compare the two participant groups in terms of gait parameters. The results of this analysis, as well as the participants' demographic characteristics, are shown in Table 2. The results of the F test showed that the two groups were significantly different for the following four variables:

1. For average left step length, the p-value was 0.03, ($p(x \leq F) = 0.01$). The test statistic F was 0.350, which was not in the 95% region of acceptance: [0.3958: 2.5265]. S1/S2 = 0.59, was not in the 95% region of acceptance: [0.629: 1.589]. The 95% confidence interval of σ12/σ22 was: [0.138, 0.886].
2. The p-value for time was found to be 0.00, ($p(x \leq F) = 0.000$). The test statistic F was 0.186, which was not in the 95% region of acceptance: [0.395: 2.526]. S1/S2 = 0.43, was not in the 95% region of acceptance: [0.629: 1.589]. The 95% confidence interval of σ12/σ22 was: [0.073, 0.470].
3. For walking speed, the p-value was found to be 0.02, ($p(x \leq F) = 0.988$). The test statistic F was 2.961, which was not in the 95% region of acceptance: [0.395: 2.526. S1/S2 = 1.72, was not in the 95% region of acceptance: [0.629: 1.589]. The 95% confidence interval of σ12/σ22 was: [1.172, 7.481].
4. The p-value for average stride length was 0.02, ($p(x \leq F) = 0.012$). The test statistic F was 0.342, which was not in the 95% region of acceptance: [0.395: 2.526]. S1/S2 = 0.591, was not in the 95% region of acceptance: [0.629: 1.589]. The 95% confidence interval of σ12/σ22 was: [0.135, 0.865].

Table 2. Comparison of spatiotemporal parameters between participants with and without osteoporosis taken from the smart walker, after a 10 m walk test while using the smart walker prototype. Bold *p*-values represent significant differences.

Gait Parameters	Participants without Osteoporosis	Participants with Osteoporosis	*p*-Value
	Mean ± Standard Deviation	Mean ± Standard Deviation	
Age	69.85 ± 10.17	70.85 ± 10.18	
Total Distance covered (m)	10 ± 0.00	10 ± 0.00	
The number of steps counted	19.00 ± 2.83	26.4 ± 2.65	0.69
Time (s)	14.47± 3.23	33.75 ± 7.48	**0.00**
Average Left Step Length (m)	0.49 ± 0.05	0.25 ± 0.09	**0.03**
Average Right Step Length (m)	0.51 ± 0.08	0.29 ± 0.12	0.08
Average Left Step Time (s)	0.63 ± 0.13	0.90 ± 0.21	0.15
Average Right Step Time (s)	0.68 ± 0.12	0.99 ± 0.26	0.57
Walking speed (m/s)	0.72 ± 0.13	0.31 ± 0.07	**0.02**
Cadence (steps/min)	83.49 ± 15.37	47.72 ± 12.28	0.15
Average Stride Time (s)	1.35 ± 0.23	1.83± 0.23	0.56
Average Stride Length (m)	0.99 ± 0.11	0.54 ± 0.18	**0.02**

For the rest of the parameters, the two participant groups did not differ significantly ($p > 0.05$).

The results of the 10 m walk test showed that the people with osteoporosis tended to swing their leg slowly while walking, which significantly increased the time taken to take the next step. Consequently, their right and left step time, stride time, and time to complete the walk test were prolonged as shown in Figure 8. The average stride length of the people with osteoporosis decreased by 58.82% in comparison to that of people without osteoporosis while their cadence was higher compared to the people without osteoporosis, as shown in Figure 9. Moreover, People with osteoporosis walked 20.38% slower than people without osteoporosis, as can be seen in Figure 10.

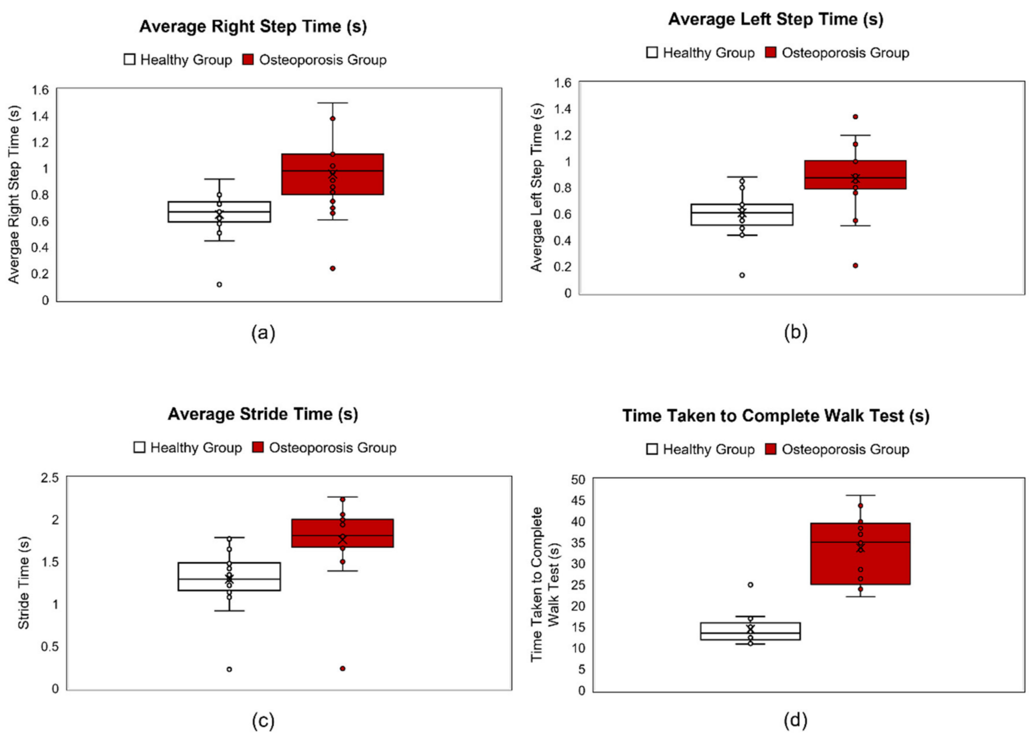


Figure 8. Graphical representation of spatiotemporal gait parameters of people with and without osteoporosis. (**a**) Average right step time, (**b**) average left step time, (**c**) stride time, and (**d**) average time taken to complete walk test.

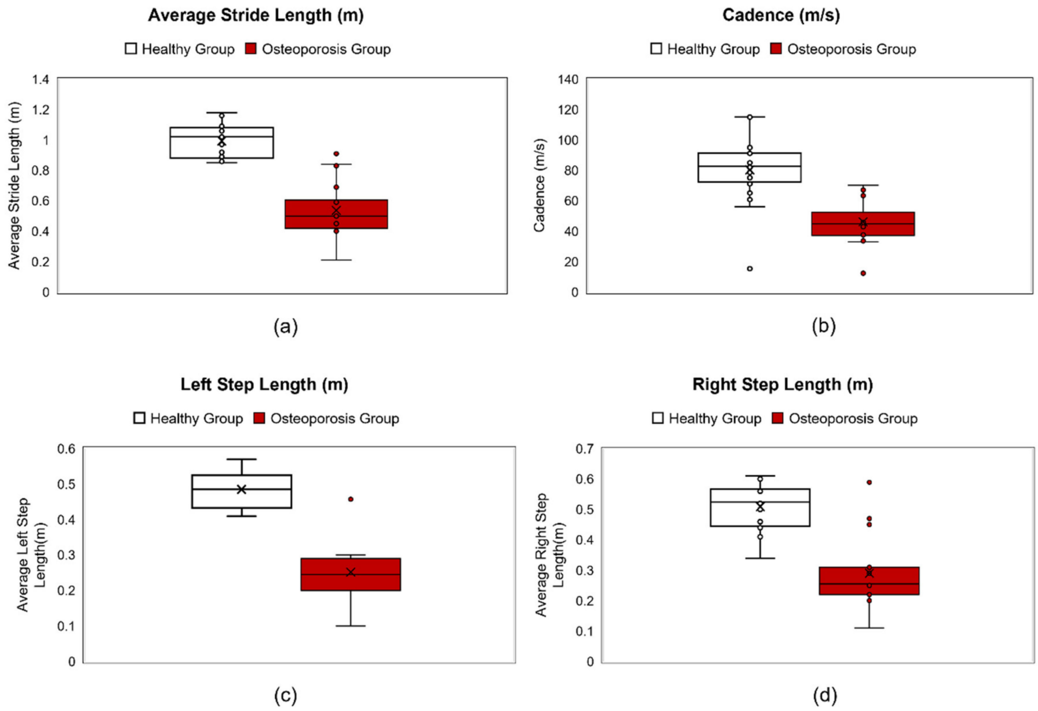


Figure 9. Graphical representation of spatiotemporal gait parameters of people with and without osteoporosis. (**a**) Average right step length, (**b**) average left step length, (**c**) average stride length, and (**d**) average cadence.

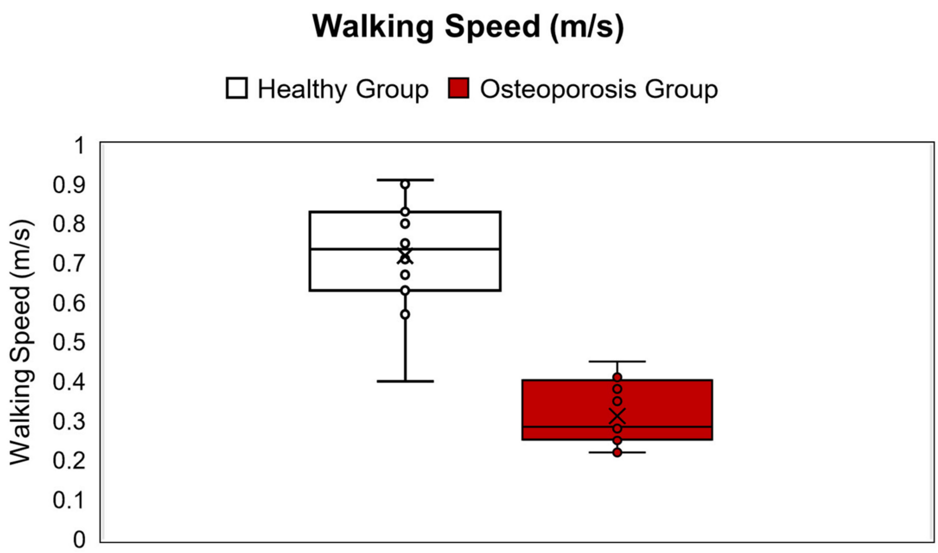


Figure 10. Average walking speed of people with and without osteoporosis.

4. Discussion

In this study, we developed and tested a smart walker prototype for monitoring gait along with providing support to users with walking disabilities. We found statistical differences in spatiotemporal gait parameters comparing people in Karachi, Pakistan, aged 50 to 90 years with and without osteoporosis. The smart walker does not need specific clothes, infrastructure, treadmills, or wearable devices. It can be used daily to assess the efficacy of therapeutic interventions provided by a physical therapist during rehabilitation process at home through self-monitoring of the number of force peaks recorded at a fixed distance. As the user's gait improves, the number of steps taken will decrease while the length of their stride will increase. The recorded data can be electronically shared with the therapist for evaluation to guide future follow-up sessions.

The gait parameters were highly affected in participants with osteoporosis compared with healthy users. It was seen that healthy adults in the age range of 50 to 90 years who do not have any significant chronic health conditions have a greater stride length, step length, cadence, and walking velocity; moreover, the stride time and average step time were lower compared with those of the osteoporotic participants because a healthy adult participant would have little or no fear of falling [35]. Thereby, people without osteoporosis took longer and a smaller number of steps to cover the 10 m marked distance compared with people with osteoporosis. The data acquired by our prototype are in accordance with the previous literature. For example, short maximal step length and slow 10 m walking speed are associated with osteoporosis in elderly women [36].

Pain due to osteoporosis may also be a factor affecting in altering spatiotemporal gait parameters. Most of our participants with osteoporosis expressed that they have trouble walking at a brisk pace and take short strides due to pain in their lower limbs while walking. Out of these patients, 16 were unable to provide us with three consecutive walk tests on the same day for the purpose of obtaining an average reading. As a result, we allocated three days to each of these patients, conducting one test per day.

A primary purpose of a standard walker is partial weight bearing of the user [37]. It was observed that the people with osteoporosis put more force on the walker while walking, in comparison to the people without osteoporosis. Since the metabolic cost of using a four-footed walker is already high [38], in the absence of any preliminary data, we cannot make a conclusive deduction. It is possible that the damage done to the bones and joints by osteoporosis increases the overall metabolic cost of walking and thus increases the force applied on our smart walker even higher [16]. Further research can explore if any correlation exists between osteoporosis and increased weight bearing.

The advantages of our proposed system include that it is portable, can be used anywhere at any time, and is economical. It has been validated with both healthy and unhealthy participants, and tests have successfully shown that the resulting gait parameters are consistent with those obtained from clinical studies. The results of our methodology are relevant to the diagnosis of people with osteoporosis by therapists. The system is easy to operate at home, allowing the user to avoid daily trips to the clinic for monitoring and enabling the recorded data to be saved according to date. By daily monitoring of the user's gait parameters, a clinician can assess the effectiveness of recommended treatment plans on a daily and weekly basis and make informed decisions about the best course of treatment for people with osteoporosis.

Usually, instrumented gait analysis via smart assistive devices is more economical in comparison to the conventional method of motion capture. Even these devices have a starting range of USD 6000 [39]. Our proposed system costs only USD 1000, making it more affordable for people in general, and for people in developing countries in particular. In addition to being cost-effective, our proposed system also offers a user-friendly interface and easy setup, eliminating the need for specialized training or technical expertise. This makes it accessible to a wider range of users, including those with limited resources or knowledge in gait analysis.

Smart Walker did not take into account how confounding variables given by various other factors might affect the gait; it is expected that in a clinical setting, people with osteoporosis also have comorbidities that impact the gait, some of them being quite common, such as joint pain, sores on feet, calluses, ingrown toenails, inner ear issues, poor lower limb circulation, poor vision, etc., whereas others are more serious, such as arthritis, herniated disk, or stroke [40]. The smart walker is wired, and users need to use the device at a fixed distance during gait monitoring; there is no direct transmission of data from walker to clinicians. This is rather a technical limitation that we considered acceptable in our prototype which focused on collecting data and identifying gait patterns related to osteoporosis. Future wireless prototypes with the ability to transmit data to the clinician will add to the functionality of the smart walker.

Further research is needed to analyze how other conditions might affect the accuracy of our proposed method and to determine if the smart walker may be useful in evaluating these conditions as risk factors for gait impairment.

5. Conclusions

The gait of people with osteoporosis observed via the proposed non-wheeled smart walker differed from that of people without osteoporosis, in terms of walking step length, stride length and the time taken to complete the 10 m walk test. The smart walker was successful in capturing gait characteristics in real-time, without the hassle of any wearable sensors or motion capture. Additional investigation is required to ascertain whether the smart walker could be a practical tool in assessing these conditions as risk factors for gait impairment and to examine how other conditions might impact the accuracy of our proposed method.

6. Patents

We filed a patent for a smart walker for lower limb disabilities at the international property organization of Pakistan (IPO).

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding authors. The dataset is not publicly available due to ethical privacy of participants involved in this study.

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