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Research Article

Gait Assessment of Younger and Older Adults with Portable Motion-Sensing Methods: A User Study

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Wearable motion sensors with built-in accelerometers have been deployed for gait assessment. This study aims at exploring gait patterns between younger and older adults using a motion-sensing system and exploring sensor technology acceptance among participants. The motion-sensing system was formed by a smart bracelet, an Android application, and a website based on Microsoft Azure. The study employed quasi-experimental, nonexperimental, and qualitative design. A total of 28 younger and 28 older adults were recruited. The gait assessment result indicated that the root mean square (RMS) acceleration increased significantly as the walking pace increased based on the right ankle sensor. Older participants usually presented a lower magnitude of acceleration patterns in the anteroposterior and mediolateral direction compared with the younger participants, while the stride regularity and variability were not significantly different between younger and older participants. User evaluation indicated that the user experience of the motion-sensing system could be further enhanced by providing feedback on the smart bracelet display, generating an analysis report on the gait visualization website, and involving family members in data sharing for older adults. Study findings demonstrated that it is feasible to use portable motion-sensing methods to measure gait characteristics among Chinese adults. Suggestions proposed through user evaluation could be of value to improve the user experience of the motion-sensing system.

1. Introduction

Wearable devices for older adults with the function of health management have become popular in recent years. Smart bracelets, such as the Jawbone UP, the Fitbit Flex, and the Garmin Vivofit, allow users to track their activities, nutrition, sleeping patterns, [1] or heart rate [2]. Moreover, many wearable devices with built-in accelerometers, such as smart bracelets [3], iPods [4], and smartphones [5], can obtain more elaborate gait characteristics to detect subtle gait changes. In a fast-aging society, using cost-effective wearable smart devices for gait assessment may increase the independence of older adults and relieve the burden of care. It is necessary to evaluate how users, especially older adults, perceive information derived from such technologies.

This study employed a motion sensor on a smart bracelet to conduct gait assessment of younger and older adults. The gait data were collected with an Android application, and the results were then visualized on a website. This study engaged younger and older adults in the evaluation process to acquire knowledge about their perceptions of the motion-sensing system. The motion-sensing system that will be discussed in this work is promising for gait assessment in home settings and for engaging the cooperation of different parties such as older adults and their family members or care givers.

More specifically, we explored the following two research objectives: (1) to test feasibility of measuring gait patterns among younger and older Chinese adults using portable motion-sensing methods; (2) to dig user requirements to improve the user experience of the motion-sensing system. The system described in this study has the potential to be expanded to a telemedicine service. Suggestions proposed through user evaluation could be of value to improve the user experience of the motion-sensing system.

2. Related Work

Gait is an important index for observing the mobility of older adults. Gait parameters, such as speed, cadence, stride length, and gait variability, are useful for the detection of frailty or fall risk of older adults [6–8]. Gait speed is viewed as an important index of physical health status and could be used as a routine tool in identifying the group that needs intervention [9–12]. Older adults with higher functional fitness were found to walk considerably faster than lower-functioning older adults [13]. In addition, other gait characteristics, such as stride length, stride frequency, gait variability, smoothness, symmetry, and complexity, were found to be predictive of falls [14, 15]. Early detection of the deterioration of gait quality may help older adults adopt timely interventions to improve their quality of life.

In recent years, many wearable devices with built-in accelerometers have been used as an innovative way to assess gait. The sensors are placed on several locations, such as the pelvis [15], the wrist [3, 16], the ankles [16, 17], the soles [18, 19], bag [20], and pocket [20]. Nishiguchi et al. [5] used an Android-based smartphone placed over the L3 region of participants to quantify gait parameters such as step frequency, step variability, balance, and stability. This study also found that the smartphone has the capability to quantify gait parameters with a degree of accuracy that is comparable to that of a triaxial accelerometer [5]. Koss et al. [4] derived multiple gait parameters from an iPod to predict age-related gait changes and found that younger adults had a more variable, less predictable, and more symmetric gait pattern compared with older adults. Meanwhile, a number of smartphone applications are available for gait assessment, such as TOHRC walk test (https://play.google.com/store/apps/details?id=ca.irrd.walktest), six-minute walk test (https://play.google.com/store/apps/details?id=com.stepic.sixminwt), and GaitUp (https://play.google.com/store/apps/details?id=com.gaitup.app.gaitup). For example, Capela et al. [21] used a smartphone worn at the midlower back and an Android application called the TOHRC walk test to derive clinically relevant six-minute walk test measures, including the total distance walked, step timing, gait symmetry, and walking changes over time. Such wearable devices provide a novel way to measure gait in day-to-day environments and are capable of identifying subtle gait changes.

Although older adults may be assisted by motion sensors in their daily life, they may encounter difficulty in using technology. Many studies have explored users' acceptance of health-related information and communication technology (ICT) products. For example, Vaziri et al. [22] designed a fall prevention system for 153 older adults to use at home to reduce common fall-risk factors such as impaired balance and muscle weakness. This study suggested that it is important to take usability as well as motivation, gender, and age into consideration when designing ICT-based fall prevention systems [22]. Puri et al. [23] explored the user acceptance of wrist-worn activity trackers among 20 Canadian community-dwelling older adults. Older adults were mostly accepting of wearable activity trackers, and wearable activity trackers were considered more personal than other types of technologies; therefore, the device characteristics such as comfort, aesthetics, and price had a significant impact on the acceptance [23].

Regarding factors influencing technology acceptance, the well-known technology acceptance model stresses the importance of perceived usefulness and perceived ease of use when designing information technology for older adults [24]. In addition, social support is necessary for older adults in the process of using information technology, particularly for older adults living in an interdependent culture, such as that of China [25, 26]. Sun and Rau [26] stated that the acceptance of personal health devices by older Chinese people was influenced by five factors: attitude towards technology, perceived usefulness, ease of learning and availability, social support, and perceived pressure. Ease of learning significantly influenced intention to use, especially for older people [26]. Social norms have a significant influence on users' acceptance of personal health devices, and Chinese users' interdependent self-construal enhances this effect [26]. Vassli and Farshchian [27] summarized motivations for and barriers to using health-related ICT among older adults. Motivations are that health-related ICT gives older adults independence, safety, and security; it allows them to socialize and manage their own health and helps them in their daily activities [27]. However, older adults need to receive assistance easily if they encounter problems in using the services and to receive training and assistance during their use [27]. Lack of privacy and safety, as well as stigma, is among the reported barriers [27].

Researchers state that "one way to facilitate older adults' adoption is through visualizations that incorporate data from smarthome sensors into relevant and insightful resources" [28]. Several studies have applied visualization to present daily data of older adults. For example, O'Brien et al. visualized sensor data from passive infrared sensors located in the living room, hallway, and bedroom of older adults' apartments to monitor changes in the movement pattern [29]. Chung et al. used a home-based sensor system to monitor the mobility and daily activities of Korean American older adults. The sensors included a motion sensor in the dining room, a hydrosensor in the bathroom, and an Internet router in the living room. The sensor data were presented on a line chart [30]. Bock et al. developed a visualization website that collected sensor data on motion, temperature, luminosity, and humidity. Activity levels were presented on a bar chart [28]. According to a study, the value of visualizations for older adults is that they make it possible to "identify patterns that they were unaware of existing" [31].

3. Materials and Methods

3.1. Participants. Twenty-eight students (14 females and 14 males) were recruited from a university, whereas twenty-eight older participants (18 males and 10 females) were recruited from a community in Jiangbei District, Chongqing, China. The inclusion criterion was that the older participants were aged over 55 years, living in the community, and able to walk independently without walking aids. People were excluded if they had any musculoskeletal, neurological disease, or painful conditions. All participants were asked to give a written informed consent prior to participation. The study ethics were approved by Tsinghua University. Participants' characteristics were collected via a background questionnaire, as presented in Table 1.

3.2. Description of Motion-Sensing System. Figure 1 presents the system architecture of the motion-sensing system. The motion sensor used in this study was a nine-axis sensor from a smart bracelet (Cavitech motion sensor, 26.5 g, 40 × 21 × 7 mm, Danco Technology Co.) with a built-in accelerometer and a gyroscope. The sampling rate is 32 Hz. The sensor can collect the acceleration and Euler angle of the $X/Y/Z$ axes. The manner in which it is worn is shown in Figure 2. The X-axis represents the anteroposterior direction, the Y-axis the mediolateral direction, and the Z-axis the vertical direction.

We initiated the motion-sensing system with the following steps. First, the smart bracelet and the smartphone were connected through Bluetooth. The sensor data were collected by an Android application that recorded the acceleration and Euler angle in real time when the participant was walking. The application was made using Unity. The motion-sensing system (http://youtu.be/fA9r5lo62Jw) was developed by Prof. Tien-Lung Sun's team from Yuan Ze University. When the Internet connection was available, the collected data were uploaded to a data collection, analysis, and visualization website based on the Microsoft Azure service (https://azure.microsoft.com). Each participant was given a code number in the database. The raw data file could be downloaded from the website in a csv format. In addition, it could be displayed on a computer or tablet on a visualization form consisting of acceleration and Euler angle patterns (Figure 3).

3.3. Procedure. Participants first signed consent forms and filled in a questionnaire regarding their age, gender, education, occupation, experience of using smartphones and smart bracelets, self-reported health status, and walking ability on a seven-point Likert scale. Their height and weight were measured as well.

Then, they wore bracelets that had been calibrated beforehand on their wrists and ankles. The participants were asked to walk ten times along a 14 m corridor at three self-selected paces: slow, normal, and fast. The initial and final 2 m were used for acceleration and deceleration. Thus, gait assessment was performed over 10 m. Two tapes were fixed on the start line and the finish line as markers. The instructions were given to each participant in a standard form, as follows: *(1) slow: walk very slowly, as if you were walking in a park; (2) normal: walk at your normal speed to the terminal line; (3) fast: walk as fast as you can to the finish line, however, do not run or take risks.* The sequence of the gait speed was randomized to avoid the effect of the order. The walking process was videotaped for verification purpose. Participants were asked to wear a pair of comfortable shoes to avoid the effect of footwear.

After the walking session, participants were asked about which parts of the body they most liked to wear the sensor on: the wrist, ankle, back, sole, or other parts of the body, on a seven-point Likert scale, with 1 indicating *do not like at all* and 7 indicating *like very much*. Then, participants were asked to rate the importance of the acceptability aspects (e.g., appearance of the bracelet and accuracy of the measurement results) of the motion-sensing system on a seven-point Likert scale, with 1 indicating *not important at all* and 7 indicating *very important*. Next, they were given a short follow-up interview. They were asked the following questions: (1) What information do you expect the motion sensor could provide you with? What is your opinion of the motion sensor used in this experiment? (2) Regarding the data visualization, we could collect your gait data and upload them to a website. Who do you think should have the authority to view your gait data (yourself, your family members, a doctor, or a nurse)? What do you think of the system and what concerns do you have? (3) Will you consider using the system in your daily life? Before the discussion, the interviewer presented and explained the visualization website to the interviewee if he or she did not understand it.

3.4. Measurement. During the gait test, participants wore motion sensors on their wrists and ankles. We found that some participants did not have the habit of swinging their arms when walking, and consequently, there were no or few waveforms in the acceleration patterns. This caused the MATLAB program to fail to detect the peak of the waveform. On the other hand, the ankle data showed periodic waveforms as the foot struck the floor. Therefore, ankle gait data were used for stride analysis. Specifically, we used right ankle data to maintain consistency. As the vertical acceleration signal of the ankle data showed more significant periodicity (see Acceleration Z in Figure 4), we used it for calculating the stride frequency, stride regularity (autocorrelation of acceleration), and stride time variability. RMS acceleration was calculated using the accelerations of three axes. The means of the gait parameters of the third and fifth trials for each walking pace were calculated as the dependent variable. Therefore, a total of $2\ (\text{walking trials}) \times\ 3\ (\text{walking paces}) \times 56\ (\text{participants}) =\ 336\ \text{trials}$ were included for analysis.

The following gait parameters were calculated:

(i) *Gait Speed (m/s)*. The gait speed was calculated as the distance (10 m) by the time elapsed.

(ii) *Stride Frequency (Hz)*. The fast Fourier transform (FFT) was used to convert the acceleration signal to the stride frequency. The stride frequency indicates the gait cycle.

(iii) *Average Stride Length (m)*. The average stride length was calculated from the speed/stride frequency.

(iv) *Stride Regularity (autocorrelation of acceleration)*. Stride regularity is calculated using autocorrelation coefficients as follows:

Table 1: Characteristics of participants in this study ($N = 56$).

Variables	Younger ($N = 28$)	Older ($N = 28$)	p
Age, mean (SD), y	24.6 (2.7)	66.1 (5.0)	<0.001*
Gender, n			
Male	14	18	0.280
Female	14	10	
Height, mean (SD), cm	169.7 (8.2)	160.6 (7.1)	<0.001*
Weight, mean (SD), kg	61.8 (10.4)	61.4 (7.3)	0.859
BMI[a], mean (SD)	21.4 (2.6)	23.9 (3.1)	0.002*
Education, n			
Primary	0	16	<0.001*
Junior	0	11	
Senior	0	1	
Undergraduate	5	0	
Graduate	23	0	
Smartphone owner, n			
Yes	28	3	<0.001*
No	0	25	
Smart bracelet experience[b], n			
Yes	16	0	<0.001*
No	12	28	
Fall history in the last year[c], n			
Yes	6	8	0.537
No	22	20	
Self-reported health status[d], mean (SD)	6.3 (0.9)	4.9 (1.2)	0.005*
Self-reported walking ability[d], mean (SD)	6.3 (0.7)	5.6 (1.3)	0.018*

Note. BMI, body mass index; SD, standard deviation. [a]Calculated as weight in kilograms divided by height in meters squared. [b]Determined by asking the question "Do you have prior experience of using a smart bracelet?" [c]Determined by asking the question "Did you fall unintentionally in the last year?" [d]Determined by a seven-point Likert scale, with 1 indicating *not good at all* and 7 indicating *very good.* *Significant at the 0.05 level.

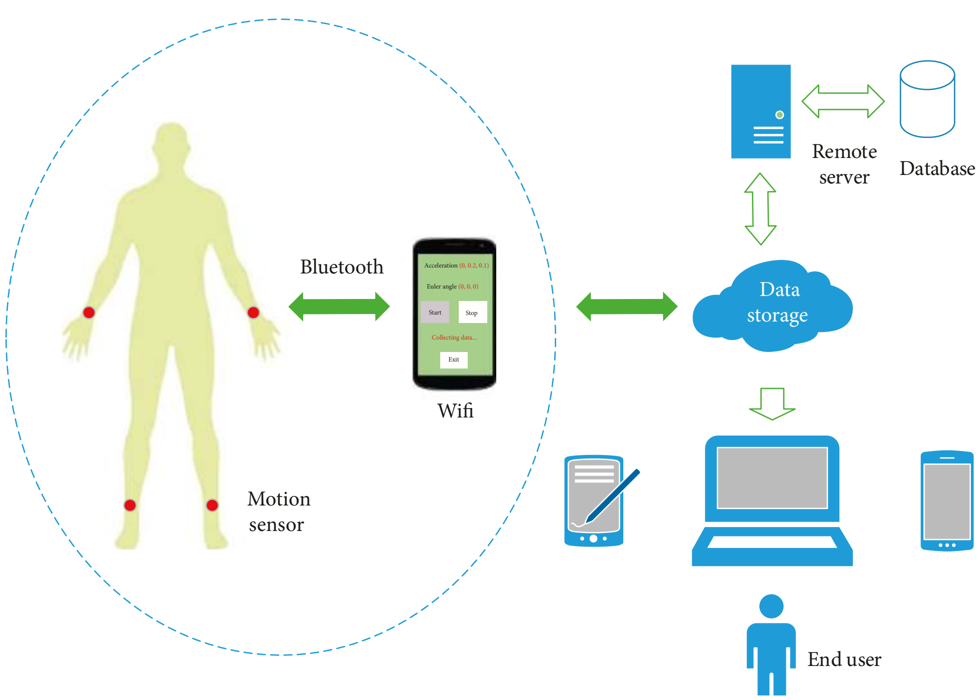

Figure 1: System architecture of the motion-sensing system.

$$R_{xx}(k) = \frac{1}{n-k}\sum_{i=1}^{n-k} x_{t_i} x_{t_i+k}. \quad (1)$$

Here, $R_{xx}(k)$ depicts the autocorrelation coefficients, which is a function of the time lag, k. $x(t)$ depicts the normalized acceleration data, which is calculated as follows:

(a) (b)

Figure 2: The manner of wearing the smart bracelet.

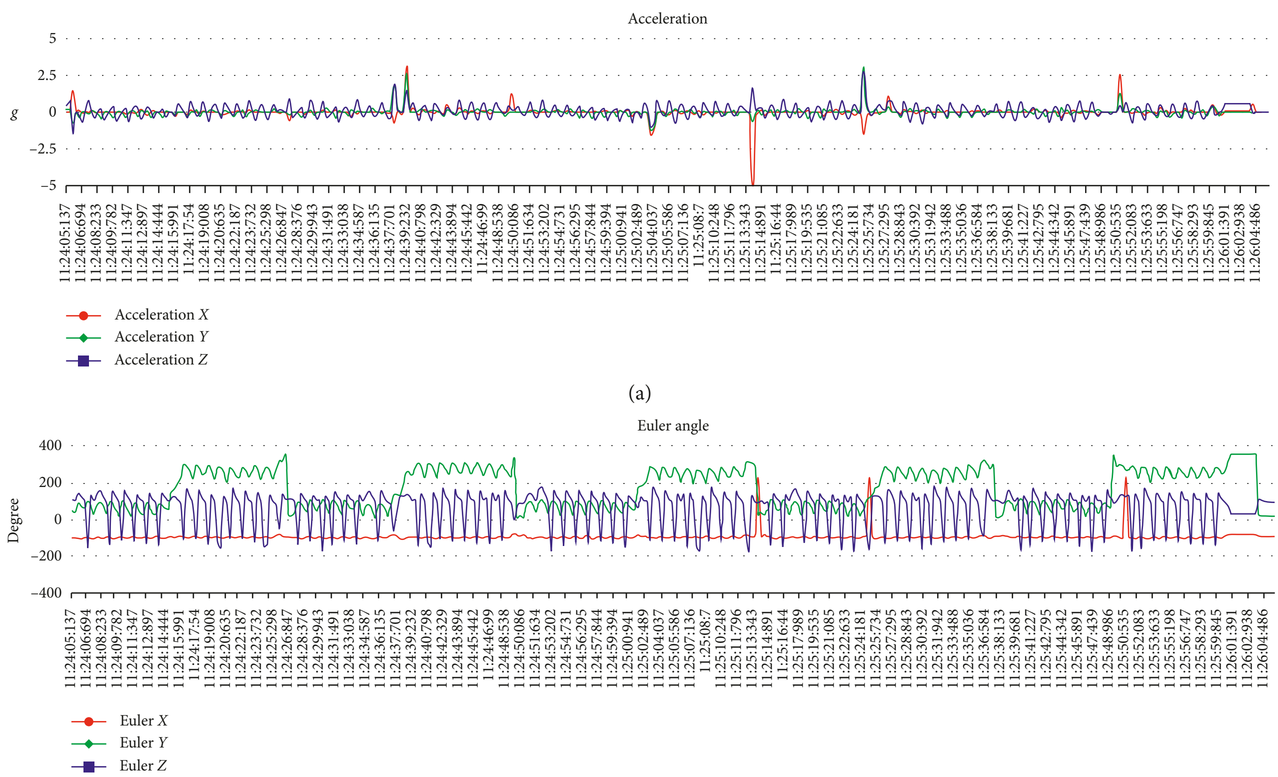

Figure 3: An example of motion-sensor data of the ankle when the participant was walking back and forth. The collected data were visualized on a cloud-based website. The website interface displayed the acceleration and Euler angle of the three axes. (a) The acceleration pattern and (b) the Euler angle pattern. The X-axis is time. The Y-axis is acceleration for (a), and the unit is gravity (g). The Y-axis is Euler angle for (b), and the unit is degree. Each waveform represented a step. An abrupt change of the Euler angle on the Y-axis (green line) indicated a turn.

$$x(t) = \frac{a(t) - a_{\text{Mean}}}{a_{\text{SD}}}, \tag{2}$$

where $a(t)$ is the acceleration data at time t and a_{Mean} and a_{SD} are the mean and standard deviation of the acceleration data.

The autocorrelation coefficient was calculated using the *xcorr* function in MATLAB. The stride regularity in this study is the peak value of the autocorrelation coefficient around a stride T [5]. The higher value of autocorrelation is associated with a better gait pattern.

(v) *Stride Time Variability*. Stride time variability was found to be an indicator of fall risk [32]. It is calculated using the coefficient of variance (CV) as follows:

$$\text{CV} = \frac{t_{\text{SD}}}{t_{\text{Mean}}}. \tag{3}$$

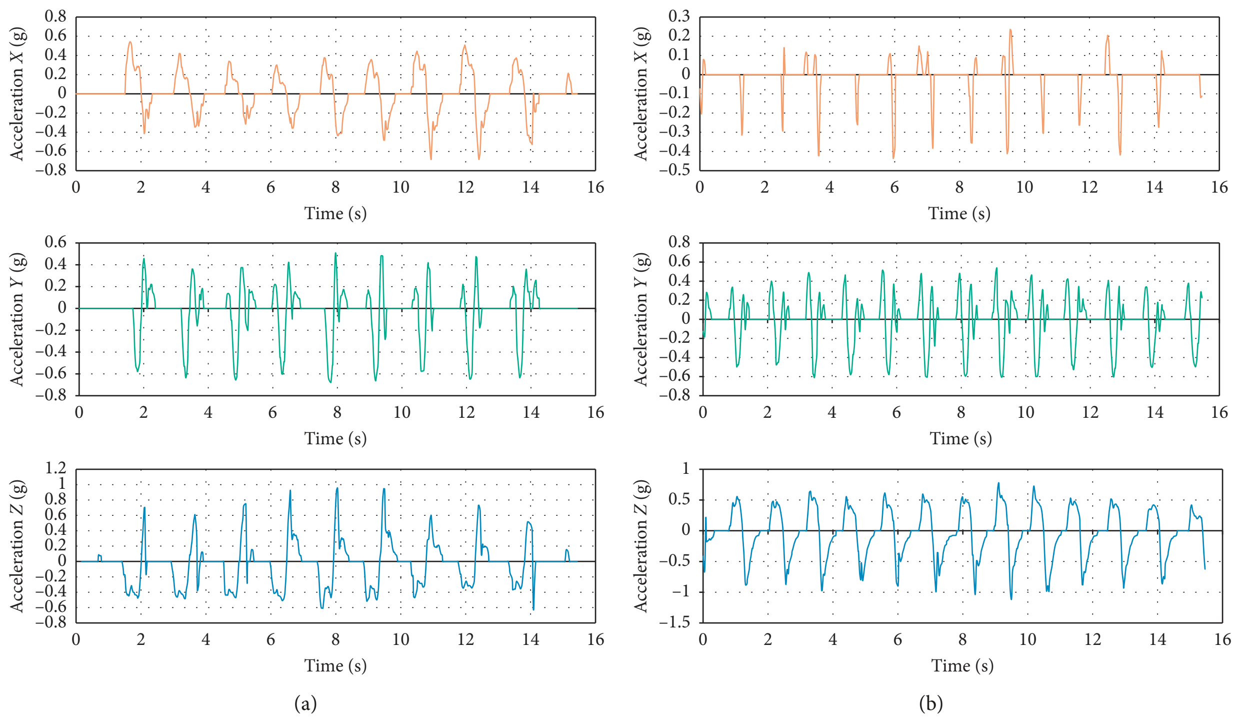

Figure 4: Acceleration patterns of ankle data of a younger participant: (a) walking speed = 1.2 m/s and an older participant: (b) walking speed = 0.69 m/s, walking at a normal pace. The scale of acceleration is in units of gravity (g). The scale of time is in units of second (s).

The positive peak of the acceleration was firstly detected by the *findpeak* function in MATLAB. The time interval from the adjacent peak was regarded as the stride time t. The CV was then calculated from the mean t_{Mean} and the standard deviation t_{SD} of the time intervals. The higher value of stride time variability is associated with a worse gait pattern.

(vi) *Root Mean Square (RMS) acceleration*. The RMS acceleration indicates the magnitude of the acceleration [33]. It is calculated as follows:

$$\text{RMS} = \sqrt{\frac{\int_{t1}^{tn} a(t)^2\, dt}{t_n - t_1}}, \tag{4}$$

where $a(t)$ is acceleration data at time t and t_1 and t_n are the start and end of the gait measurement.

3.5. Statistical Analysis. Regarding demographics, normality was assessed using the Kolmogorov–Smirnov test. For the measures that were distributed normally, independent t-tests were used; for the measures that were not distributed normally, the Mann–Whitney U test was used. Pearson's chi-square test was used to test the difference of categorical variables (i.e., gender, education, and fall history) between younger and older groups.

The motion sensor data were preprocessed using the MATLAB toolbox. As data were not constantly sampled, we adjusted the sampling rate of the acceleration signal to 100 Hz using the interpolation. A low-pass Butterworth filter with a cutoff frequency of 10 Hz was applied to filter the data. The gait parameters were then derived by a self-designed MATLAB program.

The statistical analysis of gait parameters was conducted in an R environment. The mean and 95% confidence intervals (CIs) were calculated for the averaged gait parameters for each walking pace of younger and older participants. A two-way mixed analysis of variance (ANOVA) was conducted to investigate the effect of age group and walking pace (slow, normal, and fast) on gait parameters (speed, stride frequency, average stride length, stride regularity, stride time variability, and RMS acceleration). The within-subject variable was the walking pace, and the between-subject variable was the age. After the ANOVA, if the walking pace or the interaction effects were significant, *post hoc* tests were performed using the Fisher least significant difference (LSD) test. The level of significance was set at $p < 0.05$ for all analyses.

For importance rating of acceptability aspects of the motion-sensing system, Mann–Whitney U-tests were conducted to compare the differences in attitudes between younger and older adults because the assumption of normality was not fulfilled. The recordings regarding the participants' perceptions of the motion-sensing system were transcribed by a researcher. Different researchers checked the scripts for accuracy. Content analysis was conducted to identify the requirements of the participants regarding the motion-sensing system. The derived data used to support the findings of this study are available from the corresponding author upon request.

4. Results and Discussion

4.1. Participant Characteristics. The older group had significantly higher body mass index (BMI) value, lower height, education level, self-reported health status and walking ability, less number of smartphone owners, and smart bracelet experience than the younger group. Height and BMI were distributed normally; therefore, the independent t-test was used to test the difference. Age, weight, self-reported health status, and walking ability were not distributed normally; therefore, the Mann–Whitney test was used to test the difference. The demographic information of the participants is presented in Table 1.

4.2. Effect of Age and Walking Pace on Gait Parameters. Descriptive statistics of the gait parameters are presented in Table 2. Interaction effects and main effects on gait parameters are presented in Table 3. *Post hoc* tests are presented in Table 4 if there was a significant interaction effect and Table 5 if there is no significant interaction effect, respectively.

4.2.1. Effects of Age and Walking Pace on Temporal-Spatial Gait Parameters

(1) Speed. There was a significant effect of interaction between age group and walking pace ($F_{(2,108)} = 17.11$, $p < 0.001$) on walking speed. This indicates that the younger and older adults were affected differently by the walking pace. The simple effect analysis showed that the average gait speed increased significantly from the "slow" to the "fast" pace in both age groups ($p < 0.001$). The younger participants walked significantly faster than the older participants at normal ($p = 0.011$) and fast paces ($p < 0.001$).

(2) Stride Frequency. There was a significant interaction between age group and walking pace ($F_{(2,108)} = 18.84$, $p < 0.001$) on stride frequency. This indicates that the stride frequencies of the younger and older groups were affected differently by the walking pace. The simple effect analysis showed that the stride frequency increased significantly from the "slow" to the "fast" pace in both age groups ($p < 0.001$). The younger participants walked with significantly higher stride frequency than the older participants at fast pace ($p < 0.001$).

(3) Stride Length. The interaction effect between the walking pace and the age group was not significant ($F_{(2,108)} = 0.42$, $p = 0.661$) on stride length. Average stride length increased significantly as walking pace increased ($F_{(2,108)} = 154.27$, $p < 0.001$). The LSD post hoc test indicated that there was significant difference in stride length for all pairwise comparisons ($p < 0.001$). The younger participants had a significantly longer average stride length compared with the older participants ($F_{(1,54)} = 5.88$, $p < 0.019$).

4.2.2. Effect of Age and Walking Pace on Acceleration Patterns

(1) Stride Regularity. The interaction effect between the walking pace and the age group was not significant ($F_{(2,108)} = 0.084$, $p = 0.919$) on stride regularity. The walking pace ($F_{(2,108)} = 1.03$, $p = 0.359$) and age ($F_{(1,54)} = 1.10$, $p = 0.298$) had no significant effect on the stride regularity.

TABLE 2: Mean (95% CI) of gait parameters of younger and older adults under different walking paces ($N = 56$).

Gait parameters	Younger ($N = 28$)	Older ($N = 28$)
Gait speed (m/s)		
Slow	1.01 (0.93–1.09)	0.97 (0.89–1.05)
Normal	1.34 (1.26–1.41)	1.19 (1.12–1.27)
Fast	1.79 (1.70–1.89)	1.46 (1.36–1.55)
Stride frequency (Hz)		
Slow	0.81 (0.78–0.85)	0.84 (0.81–0.88)
Normal	0.97 (0.94–1.00)	0.93 (0.91–0.96)
Fast	1.15 (1.11–1.20)	1.02 (0.97–1.06)
Stride length (m)		
Slow	1.24 (1.17–1.31)	1.14 (1.08–1.21)
Normal	1.40 (1.33–1.47)	1.29 (1.22–1.35)
Fast	1.57 (1.49–1.65)	1.44 (1.37–1.52)
Stride regularity		
Slow	0.79 (0.75–0.83)	0.81 (0.77–0.85)
Normal	0.81 (0.78–0.83)	0.82 (0.80–0.85)
Fast	0.79 (0.76–0.82)	0.80 (0.77–0.83)
Stride time variability (%)		
Slow	4.92 (4.10–5.74)	5.45 (4.63–6.27)
Normal	4.31 (3.49–5.13)	4.36 (3.54–5.18)
Fast	4.54 (3.90–5.20)	5.00 (4.36–5.65)
AP RMS (g)		
Slow	0.36 (0.30–0.41)	0.20 (0.15–0.26)
Normal	0.46 (0.39–0.53)	0.24 (0.17–0.31)
Fast	1.57 (1.49–1.65)	1.44 (1.37–1.52)
ML RMS (g)		
Slow	0.24 (0.21–0.26)	0.22 (0.20–0.24)
Normal	0.36 (0.31–0.40)	0.26 (0.21–0.31)
Fast	0.42 (0.37–0.50)	0.31 (0.26–0.36)
VT RMS (g)		
Slow	0.30 (0.24–0.36)	0.41 (0.36–0.47)
Normal	0.44 (0.36–0.51)	0.51 (0.44–0.58)
Fast	0.58 (0.50–0.66)	0.61 (0.53–0.68)

Note. RMS, root mean square; AP, anteroposterior; ML, mediolateral; VT, vertical.

(2) Stride Time Variability. The interaction effect between the walking pace and the age group was not significant ($F_{(2,108)} = 0.27$, $p = 0.761$) on stride time variability. The walking pace ($F_{(2,108)} = 2.90$, $p = 0.059$) and age ($F_{(1,54)} = 0.94$, $p = 0.337$) had no significant effect on the stride time variability. Stride time variability was relatively low in the "normal-pace" walking trial compared with that of the other conditions.

(3) Anteroposterior (AP) RMS. AP RMS indicates the magnitude of the acceleration in the anteroposterior direction. The interaction effect between the walking pace and age group was not significant ($F_{(2,108)} = 1.37$, $p = 0.257$) on AP RMS. AP RMS increased as the walking pace increased ($F_{(2,108)} = 1094.52$, $p < 0.001$). The LSD post hoc test indicated that there was significant difference in AP RMS for all pairwise comparisons ($p < 0.001$). The acceleration patterns of the younger participants had significantly higher AP RMS compared with the older participants ($F_{(1,54)} = 23.61$, $p < 0.001$).

(4) Mediolateral (ML) RMS. ML RMS indicates the magnitude of the acceleration in the mediolateral direction.

Table 3: Interaction effects and main effects on gait parameters.

Gait parameters	Walking pace	Age	Walking pace × age
Gait speed	$F_{(2,108)} = 311.35,\ p < 0.001^*$	$F_{(1,54)} = 11.49,\ p = 0.001^*$	$F_{(2,108)} = 17.11,\ p < 0.001^*$
Stride frequency	$F_{(2,108)} = 174.87,\ p < 0.001^*$	$F_{(1,54)} = 5.85,\ p = 0.019^*$	$F_{(2,108)} = 18.84,\ p < 0.001^*$
Stride length	$F_{(2,108)} = 154.27,\ p < 0.001^*$	$F_{(1,54)} = 5.88,\ p = 0.019^*$	$F_{(2,108)} = 0.42,\ p = 0.661$
Stride regularity	$F_{(2,108)} = 1.03,\ p = 0.359$	$F_{(1,54)} = 1.10,\ p = 0.298$	$F_{(2,108)} = 0.084,\ p = 0.919$
Stride time variability	$F_{(2,108)} = 2.90,\ p = 0.059$	$F_{(1,54)} = 0.94,\ p = 0.337$	$F_{(2,108)} = 0.27,\ p = 0.761$
AP RMS	$F_{(2,108)} = 1094.52,\ p < 0.001^*$	$F_{(1,54)} = 23.61,\ p < 0.001^*$	$F_{(2,108)} = 1.37,\ p = 0.257$
ML RMS	$F_{(2,108)} = 30.87,\ p < 0.001^*$	$F_{(1,54)} = 11.33,\ p = 0.001^*$	$F_{(2,108)} = 4.19,\ p = 0.018^*$
VT RMS	$F_{(2,108)} = 38.86,\ p < 0.001^*$	$F_{(1,54)} = 3.45,\ p = 0.069$	$F_{(2,108)} = 1.41,\ p = 0.249$

Note. RMS, root mean square; AP, anteroposterior; ML, mediolateral; VT, vertical. *Significant at the 0.05 level.

Table 4: Multiple comparisons of the walking pace in terms of the gait speed, stride frequency, and ML RMS.

Walking pace	Gait speed		Stride frequency		ML RMS	
	Younger	Older	Younger	Older	Younger	Older
Slow vs. normal	0.33*	0.23*	0.15*	0.09*	0.12*	0.04
Normal vs. fast	0.46*	0.26*	1.84*	0.08*	0.07	0.05
Slow vs. fast	0.79*	0.49*	3.38*	0.17*	0.19*	0.09*

Note. Numbers in the table are the difference in means. *Significant at the 0.05 level.

Table 5: Pairwise comparisons of the walking pace in terms of the stride length, AP RMS, and VT RMS.

Walking pace	Stride length	AP RMS	VT RMS
Slow vs. normal	0.15*	0.07*	0.12*
Normal vs. fast	0.16*	1.15*	0.12*
Slow vs. fast	0.31*	1.23*	0.24*

Note. Numbers in the table are the difference in means. *Significant at the 0.05 level.

There was a significant interaction between age groups and walking pace ($F_{(2,108)} = 4.19$, $p = 0.018$) on ML RMS. As to the younger group, there is a significant difference in ML RMS between "slow" and "normal" pace ($p < 0.001$) or between "slow" and "fast" ($p < 0.001$). As to the older group, there is a significant difference in ML RMS between "slow" and "fast" ($p = 0.001$). The ML RMS of the younger group was significantly higher than that of the older group at normal ($p = 0.004$) and fast paces ($p = 0.005$).

(5) Vertical (VT) RMS. VT RMS indicates the magnitude of the acceleration in the vertical direction. The interaction effect between the walking pace and age group was not significant ($F_{(2,108)} = 1.41$, $p = 0.249$). VT RMS increased significantly as the walking pace increased ($F_{(2,108)} = 38.86$, $p < 0.001$). The LSD post hoc test indicated that there was significant difference in VT RMS for all pairwise comparisons ($p < 0.001$). Age had no significant effect on VT RMS ($F_{(1,54)} = 3.45$, $p = 0.069$).

4.2.3. Summary of Gait Assessment. The gait assessment showed that walking pace had a significant influence on the acceleration patterns collected by the motion sensor. The RMS acceleration increased significantly as the walking pace increased. Older participants usually presented a lower magnitude of acceleration patterns in the anteroposterior and mediolateral direction compared with the younger participants, while the stride regularity and variability were not significantly different. The AP RMS was significantly correlated with the walking speed (Pearson $r = 0.283$, $p < 0.05$ for normal pace; $r = 0.340$, $p < 0.01$ for slow pace; and $r = 0.798$, $p < 0.01$ for fast pace). The gait assessment suggested that the AP RMS acceleration could be a good proxy for walking speed, which is considered as an important indicator of older adults' functional fitness [12, 13]. We were able to observe the acceleration magnitude through the visualization website without measuring distances. Moreover, the acceleration patterns of ankle data may miss peaks at low speed (Figure 4(b)). This was particularly the case for frail older people who walked cautiously and slowly.

4.3. User Evaluation

4.3.1. Importance Rating of Acceptability Aspects of the Motion-Sensing System. To understand the attitudes of the participants towards the motion-sensing system, they were asked to rate the importance of the acceptability aspects of the motion-sensing system. For those older adults who had difficulty in reading, the items of the questionnaire were read aloud. The researchers explained the meanings of the items to the older adults if they did not understand the questions.

As presented in Table 6, the most important aspects for older adults were as follows: the product will not harm the body (mean = 6.2, SD = 1.3), accuracy of the measurement result (mean = 6.2, SD = 1.1), and an expert can interpret the result (mean = 6.0, SD = 1.1). Meanwhile, the personal data not being observed by other people (mean = 3.6, SD = 1.7), inconspicuousness of the bracelet (mean = 3.8, SD = 2.0), and competing with others (mean = 3.9, SD = 2.0) were less important to older adults.

Compared with younger participants, older participants regarded "ability to learn how to use the bracelet" and "family support" more important. Older adults regarded

Table 6: Mean (SD) of importance rating of factors in accepting the motion-sensing system (N = 56).

Items on acceptability of the motion-sensing system	Younger (N = 28)	Older (N = 28)	p
The product will not harm the body	6.8 (0.5)	6.2 (1.3)	0.010*
Accuracy of measurement results	6.7 (0.5)	6.2 (1.1)	0.049*
An expert can interpret the data for me	5.5 (1.6)	6.0 (1.1)	0.196
Familiarize myself with gait information	5.8 (1.2)	5.6 (1.7)	0.787
Changes in the gait pattern could be observed	5.6 (1.3)	5.5 (1.5)	0.705
My ability to learn how to use the bracelet	4.5 (1.8)	5.4 (1.7)	0.044*
The cost of the bracelet	5.5 (1.4)	4.7 (1.7)	0.029*
Good appearance of the bracelet	4.9 (1.6)	4.6 (1.9)	0.603
Family support	3.6 (1.6)	4.6 (2.1)	0.029*
I feel fashionable when wearing the bracelet	4.0 (1.8)	4.3 (2.0)	0.387
Remaining anonymous when using the product	4.9 (1.7)	4.0 (2.0)	0.087
I can see information about other people	3.5 (1.4)	4.0 (2.0)	0.239
I can compete with others	3.6 (1.5)	3.9 (2.0)	0.752
Inconspicuousness of the bracelet	5.2 (1.5)	3.8 (2.0)	0.007*
Protection of the privacy of personal data	5.3 (1.7)	3.6 (2.0)	0.003*

Note. 1, *not important at all*; 7, *very important*. *Significant at the 0.05 level.

"the product will not harm the body," "accuracy of measurement results," "the cost of the bracelet," "inconspicuousness of the bracelet," and "protection of the privacy of personal data" less important than younger participants.

4.3.2. Subjective Attitudes towards the Motion Sensor. Regarding position to wear the motion sensor, both younger and older adults preferred to wear the motion sensor on the wrist rather than on the ankle, back, or sole (Figure 5). Other positions suggested by the younger participants included the upper arm (2 participants), lower arm (1), shoulder (1), finger (1), and head (1).

In terms of the participants' expectations of the motion sensor, the most reported functions included the step count (22 participants), heart rate (19), blood pressure (18), disease detection and reminders (15), and gait balance (10), as presented in Figure 6. Older participants tended to want to learn about chronic disease-related statuses, such as blood pressure (11 participants), blood glucose (5), cholesterol (3), cardiovascular disease (2), gastric disease (1), and cancer (1). Most older participants would like to learn "whether they are healthy or not." But two older participants argued that they were healthy and that health monitoring was unnecessary. One older participant stated "*I do not wish to know my health status because this may make me worry about whether I have any health issues*." Nevertheless, younger participants would like to be informed about step count (15), heart rate (13), blood pressure (7), gait balance (7), workout status (5), and sleep pattern (5). The diversity in responses was mainly due to older and younger adults' different health levels.

Regarding the appearance of the motion sensors, seven younger participants complained about the rectangular shape and the broad wrist parts; they would prefer a smoother appearance because it would make them feel "smart" in terms of appearance. On the other hand, three older participants mentioned they would accept the bracelet more readily if it looked like a traditional wristwatch. Two older participants suggested that it would be better if the smart bracelet was equipped with a screen.

4.3.3. Subjective Attitudes towards the Visualization Website. Regarding persons authorized to view the data, the participants were interviewed about persons authorized to view their gait data (themselves, family members, doctor, or nurse). The mentioned frequency would be recorded. As presented in Figure 7, older and younger participants showed different attitudes towards the visualization website about persons authorized to view the data (df = 3, χ^2 = 25.664, $p < 0.001$). An interesting finding is that older participants in this study were more willing to share data with their family members than younger participants. Twenty-two older participants and all the younger participants thought that they themselves should have the authority to view the health information. Nineteen older participants and only one younger participant were willing to share their data with family members. Regarding doctors, most of the older adults felt worried about having a medical examination; therefore, they said that they would not allow the doctors to view their health data unless it were necessary. On the other hand, six older participants and twenty-five younger participants trusted doctors and hoped that doctors would make medical diagnoses and offer suggestions by utilizing the data collected with the motion sensor.

Regarding privacy issues, thirteen younger participants and five older participants expressed their concerns about data privacy. Some younger participants felt unwilling to publicize their data with their personal information attached (e.g., facial features) but they were willing to publicize their data anonymously for use in scientific research. Five older participants were worried that the data could be utilized illegally by other people. However, some participants did not view gait information as a private form of data. Four older participants mentioned that they hoped someone could view the data and help interpret the results.

Regarding the data display form, most younger and older participants thought the current form of visualization of the

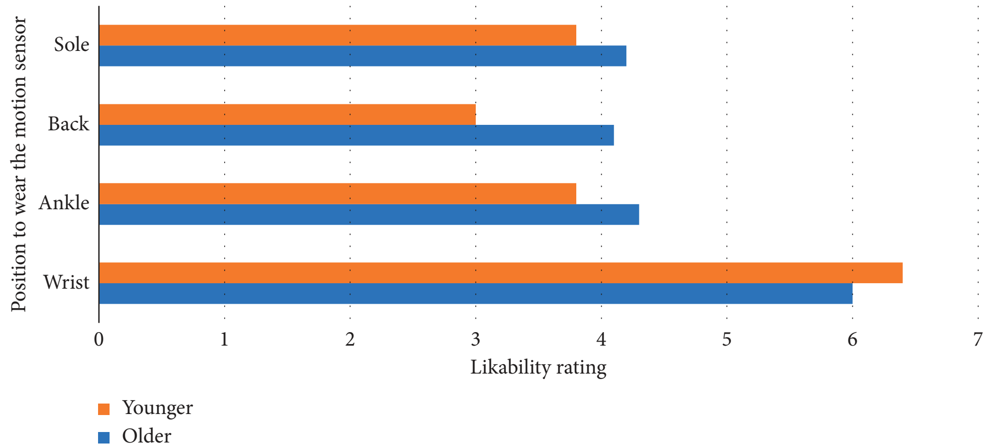

Figure 5: Participant ratings of the preferred positions in which to wear the motion sensor (1 = *do not like at all*; 7 = *like very much*).

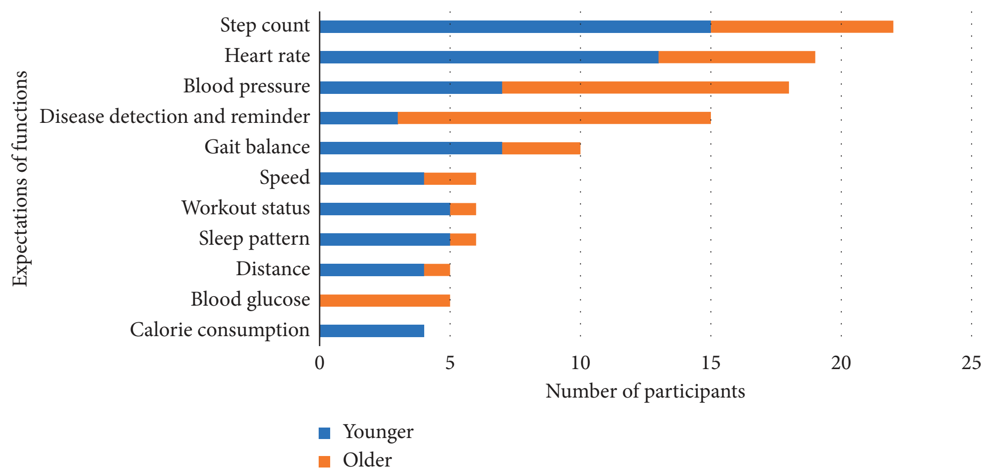

Figure 6: Most frequently mentioned expectations of the motion sensors.

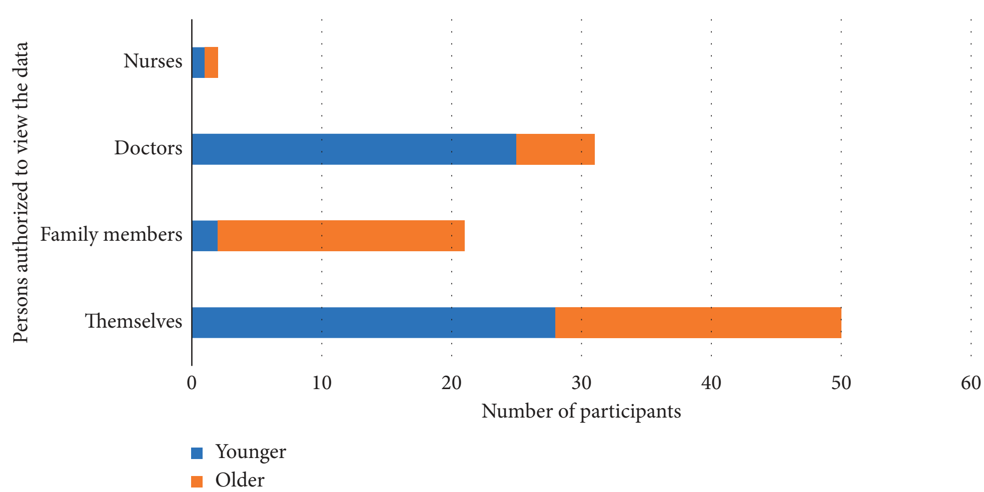

Figure 7: Persons authorized to view the data.

gait on a line chart was difficult to understand. Eight older and eight younger participants mentioned that they preferred to see graphs combined with written reports to obtain information about the results. They perceived the feedback of the gait assessment system as more like a professional report with a graph, conclusion, and doctor's advice.

4.3.4. Intention to Use. At the end of the experiment, participants were interviewed about their intention to use the system. Participants had mixed opinions towards using the system. Six older and three younger participants thought they would use the motion-sensing system in daily life. The reasons given by the participants were "*understanding more about my health status,*" "*I would like to know if I am making progress or getting worse*" (3 younger participants; 1 older participant), "*with such a product I can walk faster than before*" (1 older participant), "*it could motivate me to exercise more*" (1 younger participant), "*I can wear it as an accessory*" (1 older participant), and "*it is fun using the motion sensor*" (1 younger participant).

Eleven older and seven younger participants conveyed that they would not use the system. The main reasons given were as follows: "*there is no need to track my health status because I am healthy*" (6 older participants; 2 younger participants), "*I tend to believe doctors rather than wearable technologies*" (6 older participants), "*wearing the sensors would be a burden. I will feel more comfortable without wearing the sensor*" (2 older participants; 3 younger participants), "*the size of the sensor is too large*" (2 younger participants), "*the system could not record enough information. I expect it is a spectator with professional knowledge*" (2 younger participants).

Eleven older participants and fifteen younger participants said that their intention to use the system would depend on the situation. The reasons given were as follows: "*it is only necessary if it can track health-related data*" (6 older participants), "*if there were someone guiding me on how to use it, I would consider it*" (3 older participants), "*if I could understand the results*" (2 older participants), "*I will only use it during my leisure time, but I will not use it when I am busy doing something*" (2 older participants), "*if the measurement results are accurate*" (1 younger participant), "*I would trust the reliability only if professional organizations endorsed such a product*" (1 older participant).

4.3.5. Suggestions to Improve the User Experience of the System. Based on the user evaluations, we identified the following design recommendations to improve the user experience of the system:

(i) Older adults were interested in having more biometric information such as blood pressure, blood glucose, and cholesterol as well as gait information. Their information needs are strongly correlated with their own health statuses.

(ii) Regarding the appearance of the bracelet, a soft shape, such as that of a traditional wristwatch, would be more favourable for older adults.

(iii) Real-time feedback should be displayed on the bracelet interface. Preferably, the smart bracelet should be equipped with a screen.

(iv) The interface of the data display should be improved to enable users to understand the results better. For example, a gait analysis report is required to explain the results with graphs, conclusions, and medical advice.

(v) To reduce users' privacy concerns, identifiable personal information such as facial features should not be shown.

(vi) Older adults in this study were willing to share data with their family members, therefore, involving family members may facilitate the process of using the system.

5. Conclusion

This study suggested that it was feasible to conduct gait assessment using a portable motion sensor on a smart bracelet. We could place it on the ankle to measure gait parameters. The visualization website could provide health-related information about gait performance. For example, stride frequency indicates the gait cycle; stride time variability is commonly considered as a fall-risk predictor [14]. Slow gait speed at the usual pace was considered as a predictor of adverse outcomes [9], which is reflected in an acceleration pattern with lower amplitude (RMS acceleration in this study). Stride regularity indicates the similarity of the gait patterns. These results could be used as gait indicators for self-management.

Gonzálezlandero et al. [2] used a smart bracelet Sony 2 for measuring heart rate and Google Fit Application Programming Interface for storing data and Android for managing data, while this study have explored the use of the smart bracelet to measure gait characteristics based on its embedded motion sensor. These studies suggested that smart bracelets could be applied to measure several body features as health management indicators. The data could be stored in the cloud for further analysis. Such features would benefit older adults or rehabilitation patients as they could observe any improvement or deterioration for a certain period, for example, when they take exercises or conduct a rehabilitation program.

There are several suggestions for improving the user experience of the motion-sensing system. First, the appearance of the smart bracelet could be improved to increase user acceptance. Older adults tend to relate the smart bracelet to a traditional wristwatch. They wanted to view real-time feedback on the display. Second, both younger and older adults found the visualization of gait information difficult to understand because there was no summary to provide information about the results. The interface of the visualization website should be improved to enable users to understand the results better. For example, a report on the gait is necessary to explain the results with graphs, conclusions, and medical advice. In addition, we found that most of the older adults were open to the idea of sharing their gait information with their family members rather than doctors or nurses. Family support is especially important for older Chinese users, because Chinese people have interdependent self-construal and tend to rely on each other [26]. Therefore, involving family members might facilitate use of the system among older adults. These suggestions could be of reference value for practitioners.

In conclusion, it is feasible to use portable motion sensors on smart bracelets and smartphones to measure gait characteristics. The user experience of the motion-sensing system could be further enhanced by providing feedback on the display of the smart bracelet, generating an analysis report on the gait visualization website and involving family members in data sharing for older adults.

Data Availability

The derived data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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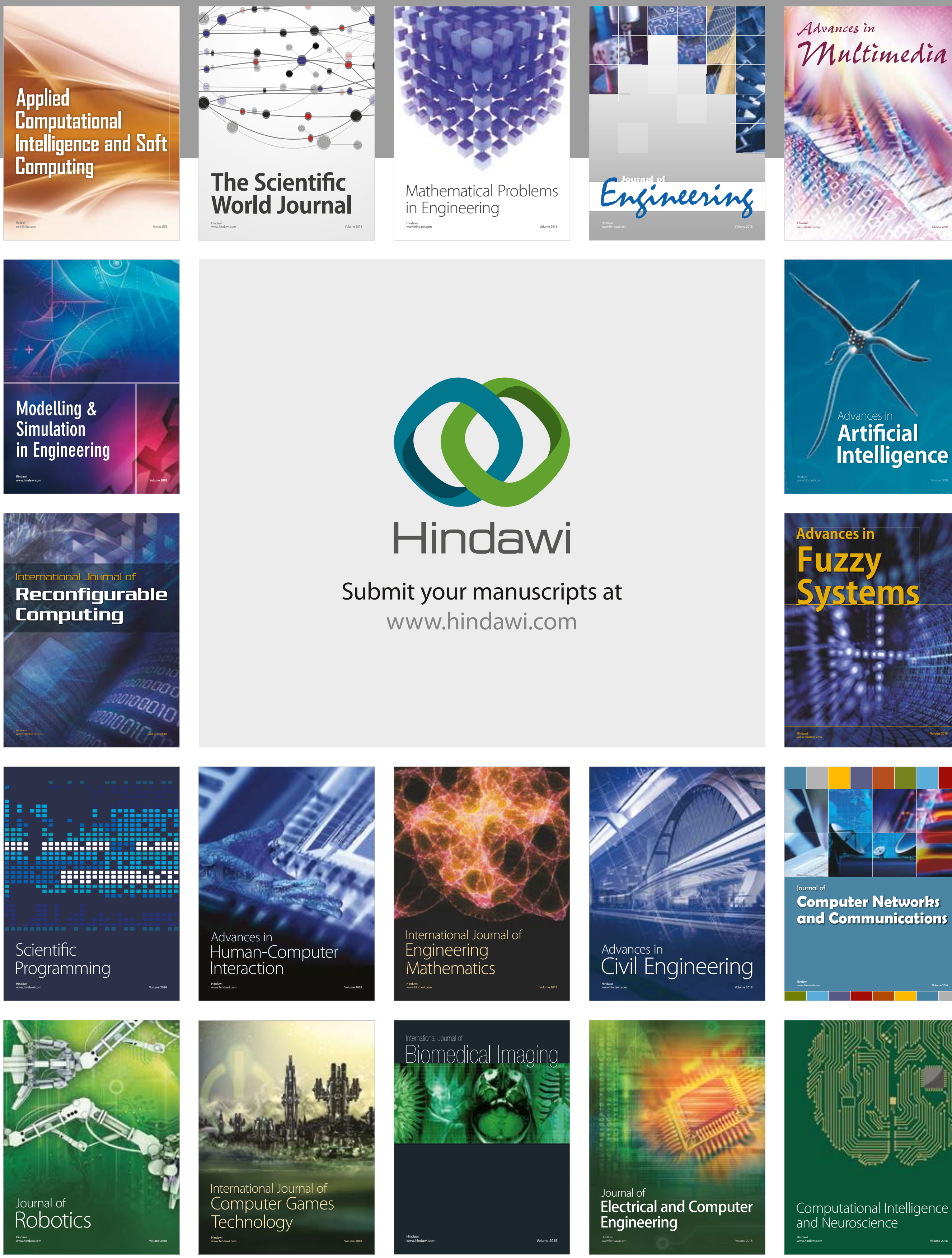
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