Searching for Stability as we Age: The PCA-Biplot Approach

Renata Noce Kirkwood[a,b,*], Scott C.E. Brandon[b,c], Bruno de Souza Moreira[a] and Kevin J. Deluzio[b,c]

[a]*Graduate Program in Rehabilitation Science, Universidade Federal de Minas Gerais, 6627 Antônio Carlos Avenue, Belo Horizonte, Minas Gerais, 31270-901, Brazil*

[b]*Department of Mechanical and Materials Engineering, Queen's University, McLaughlin Hall, 130 Stuart Street, Kingston, Ontario, K7L 3N6, Canada*

[c]*Human Mobility Research Centre, Syl & Molly Apps Medical Research Centre, Kingston, General Hospital & Queen's University, Kingston, Ontario, K7L 2V7, Canada*

Abstract: Principal component analysis (PCA) has been successfully applied to gait data; however, interpretation of the components is challenging. An alternative is to use a graphical display called biplot that gives insights into relationships and trends of data sets. Our goal was to demonstrate the sensitivity of gait variables to aging in elderly women with PCA-biplot. One hundred fifty-one elderly females (71.6±5.0 yrs), 152 adults (44.7±5.4 yrs) and 150 young (21.7±4.1 yrs) participated in the study. Gait spatial and temporal parameters were collected using a computerized carpet. PCA-biplot, discriminant analysis and MANOVA were used in the analysis. PCA-biplot revealed that elderly females walked with lower velocity, shorter step length, reduced swing time, higher cadence, and increased double support time compared to the other two groups. The greatest distances between the groups were along the variable step length with the elderly group showing a decrease of 8.4 cm in relation to the younger group. The discriminant function confirmed the importance of principal component 2 for group separation. Because principal component 2 was heavily weighted by step length and swing time, it represents a measure of stability. As women age they seek a more stable gait by decreasing step length, swing time, and velocity. PCA-biplot highlighted the importance of the variable step length in distinguishing between women of different age groups. It is well-known that as we age we seek a more stable gait. The PCA-biplot emphasized that premise and gave further important insights into relationships and trends of this complex data set.

Keywords: Gait, Principal Components Analysis, Biplot, Elderly, Balance, Step Length.

1. INTRODUCTION

An efficient gait pattern is characterized by stable and adaptable forward progression throughout both stance and swing phases [1]. Humans first learn how to control balance after the onset of independent walking, and progressively develop a refined locomotor pattern that becomes similar to an adult's gait by the age of 7 [2-4]. From the time gait matures in childhood it remains stable until the age of 55-60 years, when gait adaptations begin in response to the aging process [5-7].

Summary statistics such as mean, variance and correlations are normally used for gait comparisons with respect to temporal and distance parameters such as velocity, step length, cadence, base of support, and duration of the gait phases [8]. Inferential statistical tests are important in defining statistical significance difference (e.g. p-values), but provide limited additional information in how the variables are related to each other, and how the groups and subjects behave among themselves. In addition, gait variables are highly correlated [9], have a temporal dependence [10], interact in a complex linear fashion, and also demonstrate higher variability as age increases [11, 12]. For example, velocity is a function of step length and cadence; in addition, as we increase our velocity the ratio changes between stance and swing, with stance time becoming shorter than swing time. As a result, new statistical approaches to analyse quantitative gait data have been proposed [10, 13, 14]. Among them, principal component analysis (PCA) has been recognized as a powerful tool to extract useful information from highly correlated data [15]. The purpose of PCA is to reduce the original, correlated data to a smaller set of uncorrelated variables called principal components (PCs). This reduction is accomplished with minimal loss of clinical information because the principal components are ranked such that the first few components capture most of the variation present in the original data, and subsequent components can be discarded [16]. Each retained principal component represents a weighted linear combination of the original variables; the larger the loading of a specific variable, the more influential this variable will be in the structure of that PC. However, it may be challenging for researchers to extract clinically relevant information based solely on the relative weighting of each original variable within a given principal component.

*Address correspondence to this author at the Department of Kinesiology and Physical Education, Wilfrid Laurier University, 75 University Avenue West, Waterloo, Ontario, N2L 3C5, Canada; Tel: 519 884-0710 x4156;
E-mails: renata.kirkwood@gmail.com, rkirkwood@wlu.ca

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An alternative strategy for interpreting the structure of the PCs is to use a graphical visualization called biplot [17-19]. A biplot is a projection of a multidimensional data matrix that simultaneously displays both the observations and the variables of the matrix, where the observations are shown as points and the variables are shown as vectors [20, 21]. The biplot is a useful tool in exploring the structure of the data since not only provides graphic approximation to complex data sets, but also gives insight into relationships, trends and clusters between the variables and groups in the study [22]. Although the biplot methodology has been applied in rehabilitation studies [23, 24], to our knowledge there is no description of these techniques in evaluating gait spatial and temporal parameters.

Therefore, the aim of this study was to describe the spatial and temporal gait variables among a group of elderly, adults and young female individuals by applying PCA together with biplot graphical statistical approach. Through the PCA-biplot methodology our goal is to demonstrate the nature and role played by these variables in understanding gait changes in women during life span.

2. METHOD

2.1. Participants

Three groups of females elderly, adults and young individuals were recruited from the general community of the city of Belo Horizonte, Brazil, according to the following inclusion criteria: 1) for the female elderly group, age ≥ 65 years, 36 to 56 years for the female adult group and the female young group selected for the study was between 18 and 26 years of age; 2) all individuals were able to walk independently without human or mechanical assistance. The exclusion criteria for all groups included: 1) diagnosis of any musculoskeletal or neurological disorder that could compromise the gait pattern; 2) history of previous surgery or fractures of the inferior limb in the last 2 years.

Anthropometric characteristics including age (years), height (m), mass (kg) and body mass index (kg/m^2) were collected in order to describe the sample. This study was approved by the Universidade Federal de Minas Gerais Research Review Board (ETIC n^o 644.0.203.000/10) and all participants provided written consent prior to data collection.

2.2. Gait Spatial and Temporal Parameters

Gait measurements were collected with a 5.74 m computerized walkway system (GAITRite®, CIR systems, USA). Seven gait parameters: velocity (cm/s), cadence (steps/min), step length (cm), base of support (cm), swing time (s), stance time (s), and double support time (s) were collected with the subjects at their preferred walking speed. Participants started walking 2 m before the mat and continued 2 m past the mat to allow for acceleration and deceleration. Six trials with good data quality, and an average of 3 strides per trial, were saved for each subjects' data analysis.

2.3. Statistical Analysis

PCA was used on a set of multidimensional correlated data, Y, represented by n subjects' observations on p variables. In the present study, the $n \times p$ data matrix Y consisted of n = 453 observations on p = 7 gait variables described previously. The variables were standardized to unit variance to eliminate any undue influence on the PCA and mean-centred to maximize the variance [16]. PCs were extracted from the mean-centred standardized data matrix through a method called diagonalization that realigns the original data into a new coordinate system [25]. The data is thus transformed from n observations on p, correlated variables, to n subject scores on k, uncorrelated PCs, where $k \leq p$.

For a given PC, each subjects' score represents the distance each individual is from the mean score [26]. A lack of correlation between the PCs means that each PC measures a different feature of variance within the original data [27]. Because the new set of k PCs is ranked in order of decreasing variance explained, it is possible to identify the largest independent features of variance within the original data [15, 26]. Finally, since each PC is structured as a weighted combination of the original correlated variables, it is possible to interpret the clinical meaning of each PC based on the relative weighting of the original variables. For a given PC, a large score will correspond with large observations for the primary contributing original variables. To simplify interpretation of the PCs, only primary contributing variables were considered; the absolute value of the weighting coefficient for each primary contributing variable was greater than half of the maximum coefficient for the relevant PC [16]. The resultant PC scores were submitted to a stepwise discriminant analysis to determine which PCs could discriminate the groups.

2.3.1. Biplot Methodology

The biplot uses the diagonalization method to give a graphical display its dimensional approximation [17, 28]. For an illustrative purpose, Figure **1** shows a simplified example of a PCA-biplot.

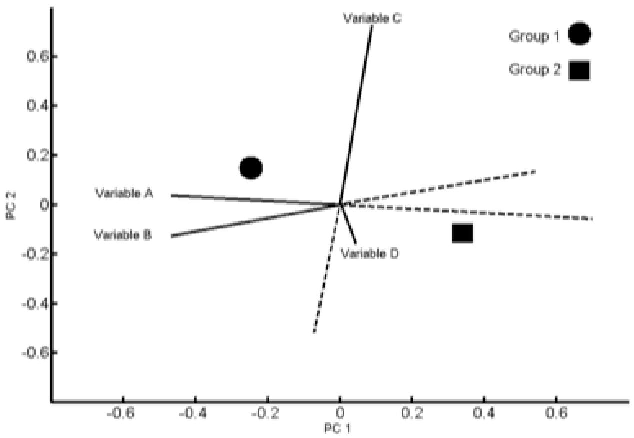

Figure 1: Example of a PCA-biplot of a data matrix. The description of the biplot follows on the text.

In this example, a raw data matrix *X* consisted of *n* subject observations (divided into two groups) on 4 variables (variables A, B, C and D). The two axes of the biplot represent the first (PC1) and second (PC2) PCs of *X;* therefore, the biplot is used to understand how the subjects are distributed in the 2-PC model, and what each PC means in terms of the original variables. In this example, the average PC scores for Group 1 and Group 2 are represented by a circle and square, respectively. PC scores follow a standard normal distribution, which means the transformed observations have zero mean. The biplot differs from a simple scatterplot in that the original variables A, B, C and D are also shown in the plot as vectors. Since the variables are standardized and the vectors scaled to have a unit length in the original dimensional space, the origin of the vectors is equal to zero.

Interpretation of the biplot involves observing the lengths and directions of the variables. The length of each vector approximates the amount of variance in each original variable that is captured by the 2-PC model, where longer vectors indicate higher variance [18, 29]. In the example, variable C has the largest proportion of its variance explained. Conversely, when a vector length is much less than unity it is an indication that the variable is not well represented in the space [30]. In the example, variable D is not well represented using only PC1 and PC2; the contribution of variable D must be analyzed by adding additional PCs to the model.

The relative angle between any two variables' vectors represents their pairwise correlation; the closer the vectors are to each other (< 90°), the higher their correlation [21, 23]. When vectors are perpendicular (angles approaching 90° or 270°), the variables have a small or no correlation. Angles approaching 0° or 180° (collinear vectors) indicate a correlation of 1 or -1, respectively. Thus, variables A and B show a strong positive correlation in the example on Figure **1**.

Similarly, the directions of the variables' vectors with respect to the axes indicate the PC to which each variable is most strongly related. In this example, variables A and B contributed more to PC1 and variable C to PC2. The projection of variables A and B on PC1 show large negative values, while the projection of variable C on PC1 shows small positive value. Therefore, variables A and B are opposite in direction in relation to variable C in the PC1 dimension, although variable C has only a small contribution. It should be noted that the sign of the variables on any PC is arbitrary. If we reverse all the signs in the component, the variance as well as the orthogonality will be unchanged; therefore the interpretation will remain the same [16].

Another important characteristic that can be extracted from the PCA-biplot is the spatial proximity of the groups in relation both to each other and to a set of variables. In the example, the projection of Group 1 onto the vector for variable A falls on the positive (solid line) direction of the variable' vector, which means that subjects in Group 1 had higher than average values for variable A. Conversely, the projection of Group 2 onto variable A falls on the opposite (dotted line) direction; therefore, the average value for Group 2 is less than the mean for variable A. In addition, Groups 1 and 2 are more distant from each other when projected onto variable A than on any other variable. This indicates that variable A is the most important variable for group separation in the 2-PC model. Therefore, the PCA-biplot is an important tool to help determine the general features of the data [30]. The mathematical explanation for constructing a PCA-biplot has been described elsewhere in detail [17-20].

In the present study, we modified the PCA-biplot originally developed by Gabriel in 1971 [17], to scale all variables' vectors by a constant factor such that the distances between groups and the vector lengths are on the same scale. Our objective was to enhance the visible distance between the groups in order to interpret which dimension and variables are most important for group separation. Because the vectors have been scaled for visualization, we no longer compare the vector lengths to unity to determine whether the vectors are well-represented by the model. Instead, we have added a scale in the bottom left corner of the graph (Figure **2**) to indicate how well each variable is represented in the biplot. The relative length, direction, and correlation of the vectors are still interpreted on the same way.

2.3.2. PCA-Biplot and MANOVA

To interpret the PCA-biplot results with an inferential test, multivariate analysis of variance (MANOVA) was conducted with the gait variables. MANOVA is the multivariate analogue to Hotteling's T_2 designed to look at several dependent variables using the variance-covariance between variables to test the statistical significance of the mean differences. If the results are significant, it follows a post-hoc test, such as the Scheffé test used in the present study, to determine the differences among the groups. The post-hoc tests adjust the significance levels to account for multiple comparisons [31]. All tests were analysed within a 0.05 significance level.

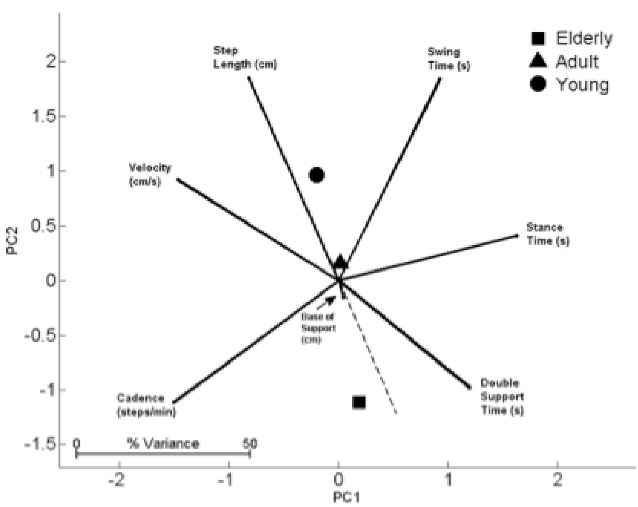

Figure 2: PCA-biplot of the gait variables and the average score of the female elderly, adult and young groups.

3. RESULTS

The anthropometric and gait parameters of the elderly, adult and young female groups with the range, mean, standard deviation (SD) and the *p*-values from the MANOVA test are shown on Table **1**. PC analysis resulted in three components that explained 88.4% of the data variance: 49.1% for PC1, 24.8% for PC2, and 14.5% for PC3. Table **2** shows the results of the PC analysis with the proportion of variance explained.

The configuration of the modified PCA-biplot is shown on Figure **2**. The variables lengths are well represented in the dimensions, except for the variable base of support with a short vector meaning a relatively small variance was captured compared to the other variables. Further analysis, not represented here, showed that the variable base of support is entirely represented by PC3 (97.0%). Therefore, variation in base of support is independent of all the other gait variables in the study. The highest relative variance, indicated by the longest vector, is attributed to the variable swing time, followed by step length and stance time. PC1 is heavily weighted by stance time, cadence, velocity and double support time and PC2 by step length and swing time (Table **2**). Velocity and step length show higher correlation compared to the other pairwise variable comparisons (Figure **2**). Velocity and double support time are highly negative correlated, since these vectors are nearly in opposite direction from the origin. Step length has virtually no correlation with cadence and velocity is uncorrelated with swing time.

The elderly, adult and young groups are represented by symbols on the modified PCA-biplot. The biplot was not used to test for statistical significance, but it clearly demonstrated possible relationships within the data. Elderly females are furthest apart from the other two groups and located on the inferior half of the biplot. The projection of the elderly group onto the variables shows that, on average, elderly females walk with lower velocity, step length, and swing time, and higher cadence and double support time compared to the other two groups. Subjects in the adult group, compared with subjects in the young group, walk with slower gait velocity, shorter step length, reduced swing time and double support time. The projection of both groups onto the variable cadence is lower compared to the elderly group. Regarding the variable stance time, all three groups share the close same pattern since the projection of all the groups is near the origin of the variable. The projection of the groups on the variables shows that the greatest distances between the groups are along the variable step length; therefore, step length is of primary importance in group separation.

The Hoteling's trace statistic results (Table **1**) show a significant effect of group on the gait variables investigated, $T = .85$, $F(12,888) = 31.4$, $p = .0001$. Similarly, as interpreted with the modified PCA-biplot, the variables gait velocity, step length, swing time and double support time were significantly different

Table 1: Range, Mean, Standard Deviation (SD) and *p*-Value of the Anthropometrics and the Spatial and Temporal Variables Comparison Among the Elderly, Adults and Young Groups (N = 453)

Characteristics	Groups			*p-value*
	Elderly N = 151	**Adults N = 152**	**Young N = 150**	
Anthropometrics				
Age (years), range Mean (SD)	65 to 85 71.6 (5.0)	36 to 56 44.7 (5.4)	18 to 26 21.7 (4.1)	.0001[a] .0001[b] .0001[c]
Body mass index (kg/m^2), range Mean (SD)	18 to 38 27.0 (4.3)	18 to 47 27.6 (5.1)	16 to 33 22.0 (2.7)	.471[a] .0001[b] .0001[c]
Gait measures				
Velocity (cm/s), range Mean (SD)	91 to 174 127.7 (16.1)	94 to 187 133.4 (15.5)	96 to 182 139.3 (14.7)	.007[a] .0001[b] .004[c]
Cadence (steps/min), range Mean (SD)	103 to 140 120.3 (7.6)	96 to 147 117.6 (7.9)	100 to 137 116.1 (6.7)	.006[a] .0001[b] .244[c]
Step length (cm), range Mean (SD)	49 to 79 63.6 (6.0)	56 to 87 68.0 (5.8)	56 to 89 72.0 (5.4)	.0001[a] .0001[b] .0001[c]
Base of support (cm), range Mean (SD)	1 to 16 7.4 (2.6)	2 to 18 7.7 (2.2)	3 to 13 8.2 (2.3)	.571[a] .015[b] .179[c]
Swing time (s), range Mean (SD)	.30 to .50 .39 (.03)	.40 to .50 .41 (.03)	.40 to .50 .42 (.02)	.0001[a] .0001[b] .001[c]
Stance time(s), range Mean (SD)	.50 to .70 .61 (.04)	.50 to .80 .61 (.05)	.50 to .70 .61 (.04)	.999[a] .998[b] .993[c]
Double support time (s), range Mean (SD)	.20 to .30 .22 (.03)	.10 to .30 .20 (.04)	.10 to .30 .19 (.03)	.0001[a] .0001[b] .035[c]

MANOVA *p*-value significant at $p < .05$; [a] = elderly x adults; [b] = elderly x young; [c] = adults x young.

between the groups. Cadence was significantly different between the elderly and the adult and young groups and stance time showed no difference among the groups. Although, the variable base of support wasn't analysed within the biplot, a significant difference was found only between the elderly group and young group, with the first showing a narrower base of support compared to the young group.

In order to determine how the groups differed with respect to the PCs scores, we conducted a discriminant function analysis. The first discriminant function was statistically significant, $\Lambda = .531$, X^2 (6, N = 453) = 284.6, $p < .0001$, but the second discriminant function was not ($p = .131$). The standardized discriminant function showed that Function 1 was heavily loaded by PC2 (.99) scores followed by PC3 (.28) and PC1 (.08). Therefore, the largest distance observed in the biplot in the direction of PC2 is supported by the discriminant analysis, showing that PC2 is the most important component in group separation.

In order to explore the behavior of the groups in relation to the structure of PC2, we analyzed the contribution of the variables to PC2 to determine its clinical meaning. PC2 was heavily loaded by the variables step length, swing time and velocity going in a positive direction, followed by cadence and double support time going in the opposite direction (Table **2**).

Table 2: Loading Vectors Showing the Variable Contribution to Each Principal Component and the Percentage of Total Variation

Variables	Loading vectors		
	PC1	PC2	PC3
Velocity	-.46	.29	.11
Cadence	-.48	-.35	-.01
Step length	-.26	.58	.15
Base of support	.01	-.05	.97
Swing time	.29	.58	-.07
Stance time	.51	.13	.07
Double support time	.38	-.31	.15
Cumulative percentage of total variation (%)	49.1	73.9	88.4

Thus, PC2 is a measure of stability, since increased step length, swing time and velocity and decreased cadence and double support time must generate an unsteady cycle, while the opposite pattern would generate a more stable cycle. With the objective to interpret the behaviour of the groups in relation to the dimension stability, Table **3** was built with the coefficients from PC2 represented only by signs according to the direction of the variables' vectors: positive or negative. When the projection of the average group score was on the positive direction of the variables' vector, one plus (+) sign was assigned indicating high value and two plus (++) signs indicating very high value. When the projection was on the extension of the vector, a negative sign (-) was assigned with the same emphasis as previously described; one sign (-) for low value and two signs (--) for a very low value. The interpretation shows that the female elderly group walked with a very low velocity, step length and swing time, and very high cadence and double support time. Therefore, it appears that elderly females seek for a steadier gait. The female adults showed a similar pattern from the structure of PC2 as well as the younger group, with the difference that young subjects can afford walking normally with a very unstable gait.

Table 3: Interpretation of the PC2 Loading Vectors Direction and the Result of the Projection of Each Group Average Score onto the Variables' Vectors on the PCA-Biplot

Variables	Projection of the average groups on the variables			
	PC2	E	A	Y
Velocity	+	--	+	++
Cadence	-	++	-	-
Step length	+	--	+	++
Swing time	+	--	+	++
Double support time	-	++	-	--
Interpretation of the component	Stability			

+ = high value; ++ = very high value; - = low value; -- = very low value; E = elderly; A = adults; Y = young.

4. DISCUSSION

The potential of the PCA-biplot to reveal relationships between gait spatial and temporal parameters during three different life stages was discussed in the present paper. The PCA-biplot provided a clear understanding of the multidimensional relationship and variation in the data, the overlap and separation among groups, as well as the role played by each gait variable. Although the PCA-biplot is not intended to substitute a statistical hypothesis test, the results obtained from the MANOVA could be anticipated from the interpretation of the biplot. Therefore, if the researcher is seeking for a clear view and better understanding of the data, adding the PCA-biplot graph will consequently improve data interpretation.

Gait pattern is characterized by instability phases that are important to propel the body forward and to allow lateral displacement of the body's center of mass [32]. However, as we age, loss of muscle strength and range of motion together with sensory and central impairments reduce our ability to maintain balance [8, 33]. In order to cope with increased dynamic instability and the probability of falls, biomechanical adaptations in the walking patterns of elderly individuals occur. In the present study, PC2 was able to capture a stability pattern and the PCA-biplot revealed that healthy elderly females seek for stability by shortening step length and swing time, increasing step frequency and double support time and consequently decreasing gait velocity. Recently, a study conducted in healthy adults determined that these strategies were exacerbated as a result of intentional perturbations perpetrated during gait [34]. Similarly, Latt, Menz, Fung, & Lord [35] demonstrated that stability in the medio-lateral plane during gait in young adults is best achieved by reducing step length and maintaining the usual cadence. Therefore, it appears that these strategies are naturally adopted by healthy elderly females, independently of any perturbation arising from walking.

One important contribution that the PCA-biplot revealed was the role of step length in the age transitional requirement. Since group separation was exacerbated along step length, it appears that step length is the key component for those adaptations to occur. The mean step length value difference was 8.4 cm between the female elderly and the young group, and 4.4 cm between the elderly and adult groups. Therefore, a cumulative difference of 4.0 cm in step length was observed, as we get older. Recently, Kirkwood *et al*. [36] determined that a 3.0 cm shorter step length during gait could discriminate from elderly females highly concerned about falls. It appears that step length is the flagship to the biomechanical adaptations that occur during aging. Yet, it is important to determine the limits of step length reduction that are safe to prevent falls and other age related effects on gait.

The fact that base of support appeared as a separate and isolated component is not a surprise. Many evidences today suggest that base of support it is not a hallmark in differentiating individuals who were unsteady from comparison subjects [36, 37]. Our data shows that female elderly individuals were able to adjust other kinematic variables, such as step length, cadence and swing time, to compensate for dynamic instability. The contribution of a variable to a component is quantified by its weight or correlation within the component [38]. Therefore, base of support correlated slightly with PC1 and PC2, but showed a very strong contribution to PC3, 97% (Table **2**). The discriminatory function determined that PC3 was the second most important feature to group separation, with 14.5% of variance explanation. The MANOVA test on the mean base of support values for the groups indicated significant differences only between the elderly and young groups. Female young participants walked with larger base of support compared to the elderly female group. Since a wider stride would increase the muscular demands, likely reduced in our elderly individuals, it is possible that base of support is an indirect measure of muscle force that could affect balance. It is also possible that the strategy to increase base of support would be necessary only under perturbation, as already described [34]. Nevertheless, further studies are necessary to elucidate the importance of base of support on gait stability.

5. CONCLUSIONS

This is the first study that applied PCs associated with the biplot methodology to analyse gait temporal and spatial variables in three groups of healthy individuals with different ages. Previous studies applied similar methodology in exploring multidimensional outcomes in stroke and Parkinson's participants [23, 24]. PCA-biplot revealed that healthy elderly females seek for stability by shortening step length and swing time, increasing step frequency and double support time and consequently decreasing gait velocity. This method, which identified PC2 as a measure of stability, clearly enhanced data interpretation provided by the PCA-biplot.

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