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RESEARCH ARTICLE

MULTIVARIATE ANALYSIS OF ANTHROPOMETRIC AND PHYSICAL VARIABLES OF THE 20 BEST SENEGALESE SPRINTERS SPECIALIZING IN THE 100M SPRINT

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ABSTRACT

This study seeks to identify the key determinants of performance among Senegal's top 100m sprinters using a multivariate approach. Twenty male athletes specializing in the 100m were selected based on their performance in national championships. Several anthropometric, cardiorespiratory and physical variables were measured before and during the race. The statistical analysis was based on Pearson's correlation, principal component analysis (PCA) and clustering (K-Means and Ward). The results show that variables such as 30m standing start speed ($r = 0.97$), VO2max ($r = 0.59$), and stride length ($r = 0.50$) are strongly correlated with performance. PCA reveals that 95.7% of the variance in performance is explained by five principal components. Three distinct sprinter profiles were identified. These results provide an objective basis for adapting training programs and optimizing talent detection in Senegal.

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INTRODUCTION

The 100-meter sprint, regarded as the flagship event of track and field and the ultimate symbol of human speed, has been playing a central role in the history of modern athletics since its inclusion in the first Olympic Games in 1896. Over the years, world records have continually improved, driven by advancements in technology, innovative training methods, and a better understanding of the physiological, biomechanical, and psychological factors that influence performance. Iconic sprinters such as Jesse Owens, Jim Hines, Carl Lewis, and Usain Bolt on the men's side, along with Florence Griffith-Joyner and Marlies Göhr among women, have significantly shaped the evolution and global prestige of the event. African sprinting has experienced a significant rise in recent years, exemplified by the achievements of athletes such as Ferdinand Omanyala, current African record holder with a time of 9.77 seconds, and Akani Simbine, with a personal best of 9.86 seconds. Senegal, which has been participating in the Olympic Games since 1964, has had historic highlights through athletes such as Charles-Louis Seck and Oumar Loum, the latter being a finalist at the 1993 World Championships. Nevertheless, since the early 2000s, Senegalese sprinting has stagnated, with no athlete reaching an international final and the national record (10.17 seconds) remaining well below both African and global benchmarks. These observations underscore the need to investigate the multifactorial determinants of sprint performance. The present study aims to analyze the influence of anthropometric, cardiorespiratory, and physical characteristics of Senegalese sprinters, identify the most significant correlations with 100-meter performance, and compare these findings with the profiles of world-class athletes. Such an approach seeks to generate evidence-based recommendations for the optimization of performance and the development of elite sprinting in Senegal.

IMATERIALS AND METHODS

I-1- Materials

I-1-1- Population: The study was conducted at three sites (INSEPS, Iba Mar Diop Stadium, Abdoulaye Wade Annex Stadium). The population consisted of 210 licensed sprinters. The sample included the 20 best sprinters (times ≤ 10.98 seconds).

I-1-2-Variables measured: anthropometric (height, weight, BMI, body composition), cardiorespiratory (resting HR, exercise HR, VO2max), physical (running time, speed, stride length/amplitude, strength, flexibility).

I-1-3- Key instruments:

- Coroplast 912 aluminium adhesive tape
- Small colored markers: green, yellow, red and blue to mark each 10-meter section of the 100 meters
- Fully automatic Times-Tronics Argus electric stopwatch
- Kalenji HR300 running heart rate monitors
- Decathlon Coach app
- iPhone 14 Pro Max model MQ9N3VC/A- A2893 Version 17.5.1
- My Sprint app
- My JumpLab
- Measuring instruments outside the 100m
- A stationary measuring rod, model ZT-1050A
- An impedance meter scale
- A photoelectric cell
- The track at the Iba Mar Diop stadium for the Cooper half-mile test
- A guided bar for squats

I-2- METHODS

I-2-1- Description and procedure of measurements and tests

I-2-1-1- Anthropometric variables: Height was measured using a somatometer (accuracy 0.1 cm), leg length was measured using a tape measure from the iliac crest to the floor, and weight was measured using a SECA scale (accuracy 0.25 kg). BMI was calculated using the standard formula. Body composition (fat mass, lean mass, hydration) was assessed by impedance measurement, a non-invasive method widely used in health and performance.

II-2-1-2- Cardio-respiratory variables: Heart rate was recorded at rest (radial palpation), during exercise (heart rate monitor during the 100 m), and during recovery (post-exercise analysis with the Decathlon Coach app). Maximum heart rate was estimated using the Astrand (220-age) and Tanaka (208 – 0.7 × age) formulas. Maximum oxygen consumption (VO2max) was assessed using the Cooper test (half-Cooper variant, 6 min).

II-2-1-3- Physical variables: 100 m performance was measured at the national championships (11–12 August 2023) using electronic timing (Time Tronics). Intermediate times per 10 m section were recorded using multi-angle videos analyzed with Dartfish and My Jump Lab. The average number of strides, stride length and stride frequency were calculated. Speed and acceleration were determined for each 10m interval. Performance in the 30m standing start was measured using photoelectric cells, maximum strength and lower limb power were recorded using the squat and vertical jump tests respectively, and flexibility was measured using a flexometer during a forward bend test.

II-2-2- Statistical analysis

The statistical analyses followed a progressive approach, from exploring the relationships between variables to dimensional reduction and classification.

- Pearson correlation: this method was the central step in the processing. It made it possible to evaluate the strength and direction of the linear relationships between anthropometric, physiological and biomechanical variables and performance in the 100 m. It served as a preliminary filter to identify significant variables and guide multivariate analyses.
- Univariate and bivariate descriptive statistics: these were used to characterize the distributions of variables (means, standard deviations, frequencies) and examine their basic relationships. This step facilitated the understanding of average profiles and the initial comparison between variables prior to advanced analyses.
- Normality tests (Shapiro-Wilk, Omnibus, Jarque-Bera): applied to verify the distribution of data, these tests determined whether parametric conditions were met and ensured the validity of subsequent analyses.
- Principal component analysis (PCA): used to reduce dimensionality and synthesize data, PCA highlighted the latent factors explaining performance variance and enabled multidimensional visualization of the relationships between variables.

- Clustering (K-Means and Ward): finally, unsupervised classification methods were used to group athletes into homogeneous subsets. K-Means enabled optimal partitioning, while Ward's hierarchical method provided a graphical representation of the grouping structure via a dendrogram.

IIIRESULTS

III-1-Correlation analysis for preselection of variables taken before, during and after the race.

III-1-1-Correlation analysis for preselection of variables taken before the race

Interpretation: Pre-race variables with a significant correlation coefficient (VO2max and 30m standing start speed) and a p-value of less than 0.05 show that there is a significant linear correlation between these variables and 100m performance.

Table 1: Pearson correlation coefficients and p-values for variables before the race.

Variables	r*	P-values
Age	-0.09	0.71
Weight	-0.20	0.39
standing height	0.10	0.69
long legs	0.32	0.17
BMI	-0.41	0.07
Body fat	-0.18	0.46
Skeletal muscle mass	0.10	0.68
Visceral fat index	-0.10	0.69
Body Water Index	0.09	0.71
Basal metabolic rate	-0.25	0.28
Maximum squat strength	-0.16	0.51
Pmax Sargent test	-0.45	0.05
Flexibility score	0.10	0.68
VO2max	**0.59**	**0.01**
30m sprint	**0.97**	**0.00**
Resting heart rate	-0.28	0.24
perform_100m	-	-

r*: Pearson correlation coefficient. Test not significant: if p-value > 0.05. Significant test: if p-value < 0.05. In bold: coefficients with significance and their p-value.

III-1-2-Correlation analysis for the preselection of variables taken during the race

Table 2. Pearson's correlation coefficients and p-values for variables taken during the race

Variables	r*	P-values	Variables	r*	P-values
number_of_steps	0.09	0.72	acc_30m_40m	0.42	0.06
Stride freq_	-0.33	0.16	acc_40m_50m	**-0.79**	**0.00**
stride length	**0.50**	**0.03**	acc_50m_60m	-0.37	0.11
HR_during effort	0.09	0.71	acc_60m_70m	-0.30	0.19
reaction time	0.39	0.09	acc_70m_80m	0.13	0.57
time_00m_10m	**0.91**	**0.00**	acc_80m_90m	0.08	0.73
time_10m_20m	**0.92**	**0.00**	acc_90m_100m	0.21	0.37
time_20m_30m	**0.67**	**0.00**	vit_00m_10m	**-0.89**	**0.00**
time_30m_40m	**0.59**	**0.01**	vit_10m_20m	**-0.93**	**0.00**
time_40m_50m	**0.93**	**0.00**	speed_20m_30m	**-0.67**	**0.00**
time_50m_60m	**0.93**	**0.00**	vit_30m_40m	**-0.60**	**0.01**
time_60m_70m	**0.96**	**0.00**	vit_40m_50m	**-0.93**	**0.00**
time_70m_80m	**0.92**	**0.00**	vit_50m_60m	**-0.93**	**0.00**
time_80m_90m	**0.86**	**0.00**	speed_60m_70m	**-0.96**	**0.00**
time_90m_100m	0.33	0.16	vit_70m_80m	**-0.92**	**0.00**
acc_00m_10m	**-0.89**	**0.00**	vit_80m_90m	**-0.86**	**0.00**
acc_10m_20m	**-0.86**	**0.00**	vit_90m_100m	-0.34	0.14
acc_20m_30m	0.36	0.12	perform_100m	-	-

r*: Pearson correlation coefficient. Test not significant: if p-value > 0.05. Significant test: if p-value < 0.05.
In bold: coefficients with significance and their p-value.

Interpretation: The variables taken during the race with a significant correlation coefficient and a p-value of less than 0.05 (in bold) show that there is a significant linear correlation between them and performance in the 100m.

III-1-2- Univariate descriptive statistics of preselected variables taken before and during the race

Table 3. Descriptive statistics for variables before and during the race

Variables	Number*	Mean	Standard deviation	Minimum	Q1(25%)	Q2(50%)	Q3(75%)	Maximum
VO2max	20	44.55	± 4.628	39	41	44	46.25	59
_30m sprint with _stop	20	4.126	± 0.109	3.88	4.098	4.12	4.172	4.29
stride length	20	2.175	± 0.09	1.98	2.118	2.19	2.26	2.28
time_00m_10m	20	1.954	± 0.049	1.8	1.94	1.96	1.99	2
time_10m_20m	20	1.185	± 0.047	1.1	1.16	1.165	1.212	1.26
time_20m_30m	20	0.987	± 0.025	0.92	0.97	0.98	1.002	1.03
time_30m_40m	20	0.948	± 0.014	0.91	0.95	0.95	0.952	0.97
time_40m_50m	20	0.921	± 0.019	0.88	0.917	0.93	0.93	0.94
time_50m_60m	20	0.912	± 0.022	0.87	0.89	0.92	0.93	0.94
time_60m_70m	20	0.907	± 0.018	0.87	0.897	0.91	0.92	0.93
time_70m_80m	20	0.91	± 0.019	0.87	0.9	0.91	0.92	0.94
time_80m_90m	20	0.917	± 0.02	0.88	0.9	0.92	0.93	0.95
acc_00m_10m	20	2.623	± 0.141	2.5	2.525	2.603	2.657	3.086
acc_10m_20m	20	2,823	± 0.305	2.331	2.658	2.954	3.011	3.454
acc_40m_50m	20	0.341	± 0.173	0.119	0.243	0.361	0.405	0.672
speed_00m_10m	20	5.12	± 0.135	5	5.03	5.1	5.15	5.56
speed_10m_20m	20	8.452	± 0.333	7.94	8.245	8.585	8.62	9.09
spd_20m_30m	20	10.143	± 0.265	9.71	9.975	10.2	10.31	10.87
spd_30m_40m	20	10.553	± 0.158	10.31	10.502	10.53	10.53	10.99
spd_40m_50m	20	10.861	± 0.231	10.64	10.75	10.75	10.9	11.36
spd_50m_60m	20	10.97	± 0.264	10.64	10.75	10.87	11.24	11.49
spd_60m_70m	20	11.023	± 0.217	10.75	10.87	10.99	11.143	11.49
spd_70m_80m	20	10.999	± 0.228	10.64	10.87	10.99	11.11	11.49
spd_80m_90m	20	10.905	± 0.239	10.53	10.75	10.87	11.11	11.36
100m performance	20	10.689	± 0.216	10.2	10.555	10.715	10.842	10.98

Sample size*: number of athletes; Q1(25%):1st quantile; Q2(50%): median, 2nd quantile; Q3(75%): 3rd quantile. VO2max (ml/kg/min); 30m_stop_speed (seconds); stride_length (meters); 100m_performance (seconds) Times are in (seconds). Speeds are in (meters/second). Accelerations are in (meters/second squared).

III-2- Analysis of the normality of preselected variables before and during the race: Shapiro-Wilk, Omnibus and Jarque-Bera normality tests

Table 4. P-values of the various normality tests for variables before and during the race

Normality tests		Shapiro-Wilk		Omnibus		Jarque-Bera
Variables	P-values	Normality	P-values	Normality	P-values	Normality
VO2max	0.009	NO	0.001	NO	0.001	NO
speed_30m_stop	0.150	YES	0.349	YES	0.609	YES
stride length	0.030	NO	0.359	YES	0.429	YES
time_00m_10m	0.002	NO	0.000	NO	0.000	NO
tm_10m_20m	0.053	YES	0.644	YES	0.651	YES
tm_20m_30m	0.196	YES	0.254	YES	0.583	YES
tm_30m_40m	0.001	NO	0.006	NO	0.024	NO
tm_40m_50m	0.001	NO	0.064	YES	0.127	YES
tm_50m_60m	0.035	NO	0.230	YES	0.399	YES
tm_60m_70m	0.175	YES	0.596	YES	0.621	YES
tm_70m_80m	0.710	YES	0.884	YES	0.838	YES
tm_80m_90m	0.213	YES	0.788	YES	0.753	YES
acc_00m_10m	0.001	NO	0.000	NO	0.000	NO
acc_10m_20m	0.013	NO	0.751	YES	0.773	YES
acc_40m_50m	0.071	YES	0.528	YES	0.568	YES
speed_00m_10m	0.001	NO	0.000	NO	0.000	NO
spd_10m_20m	0.086	YES	0.821	YES	0.766	YES
spd_20m_30m	0.132	YES	0.096	YES	0.287	YES
spd_30m_40m	0.001	NO	0.004	NO	0.014	NO
spd_40m_50m	0.001	NO	0.050	YES	0.106	YES
spd_50m_60m	0.027	NO	0.224	YES	0.380	YES
spd_60m_70m	0.168	YES	0.586	YES	0.609	YES
spd_70m_80m	0.655	YES	0.801	YES	0.795	YES
spd_80m_90m	0.235	YES	0.813	YES	0.769	YES
perform_100m	0.278	YES	0.305	YES	0.459	YES

Normality (YES): if p-value > 0.05. Normality (NO): if p-value < 0.05.

III-3- Bivariate descriptive statistics of variables taken before and during the preselected race: Pearson correlation analysis

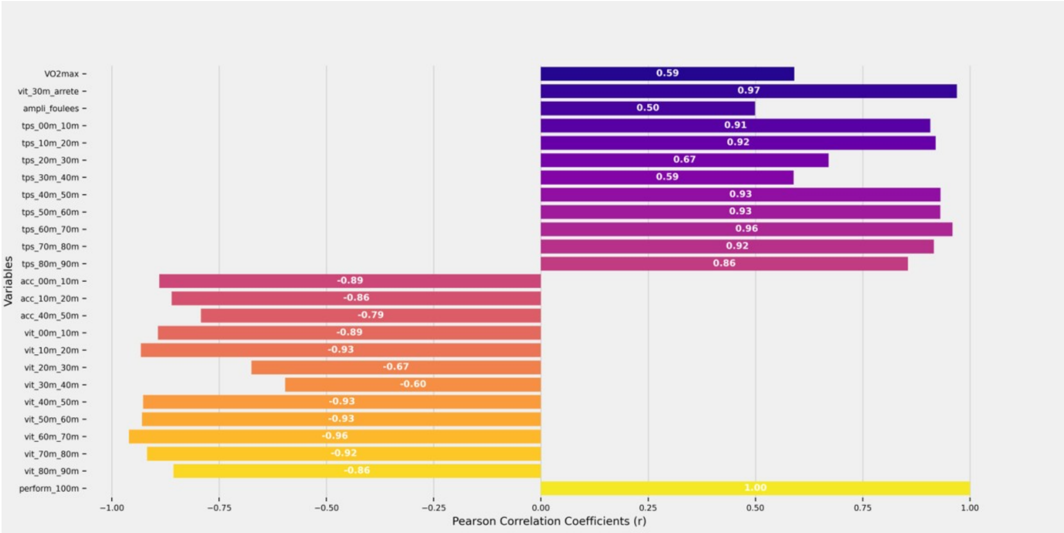

Figure 1. Pearson correlation coefficients of variables before and during the race correlated with performance in the 100m

Interpretation: Pearson correlation coefficients for preselected variables and 100m performance range from a high correlation level **(0,5 < r < 0,7)** to a very high correlation level **(0,7 < r < 1)**.

III-4-Principal Component Analysis (PCA) with pre- and during-race variables correlated with 100m performance

Table 5. Percentages of explained variance and cumulative explained variance by each principal component

Principal Components	*Explained variance (%)*	*Cumulative explained variance (%)*
PC1	73.6	73.6
PC2	10.0	83.6
PC3	5.8	89.4
PC4	4.3	93.7
PC5	2.0	95.7
PC6	1.6	97.3
PC7	0.9	98.3
PC8	0.7	99.0
PC9	0.5	99.4
PC10	0.4	99.8
PC11	0.2	100
PC12	0	100
PC13	0	100
PC14	0	100
PC15	0	100
PC16	0	100
PC17	0	100
PC18	0	100
PC19	0	100
PC20	0	100

PC: Principal Component.

Interpretation: According to the PCA results, the first five components explain 95.7% of the total variance in 100m performance.

- Component PC1 captures most of the variance (73.6%), indicating that it describes the most significant structure of Senegalese sprinters based on their performance.
- PC2 and PC3 contribute 10% and 5.8% of the total variance, respectively, so that the first three components account for 89.4% of the total variance.
- PC4 and PC5 together explain an additional 6.3% (4.3% + 2%), bringing the cumulative explained variance to 95.7% with the first five components.

The variables with the highest absolute values in the loadings matrix indicate strong relationships with the corresponding principal components.

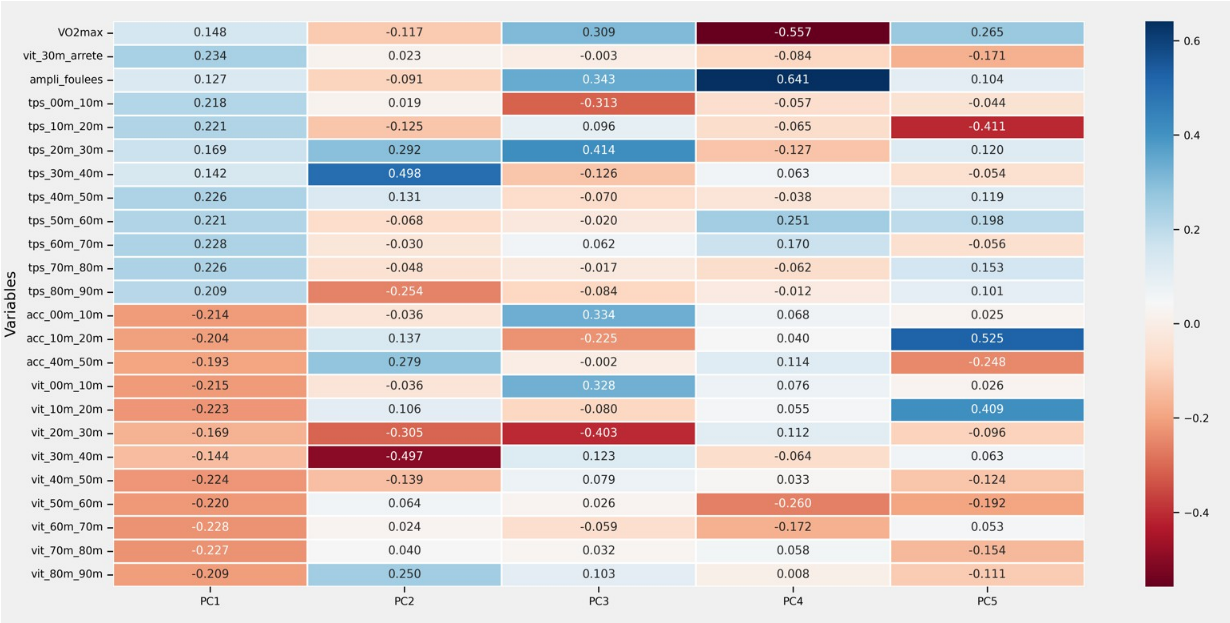

Figure 2. Matrix of variable loadings before and during the race based on principal components PC1, PC2, PC3, PC4 and PC5.

Principal component analysis (PCA) identified five key synthetic dimensions influencing the performance of Senegalese 100m sprinters:

- **PC1** reflects **overall movement speed**, dominated by speed over 30m from a standing start (*30m_sprint with stop*- coefficient 0.234), in relation to segment speeds and final performance.
- **PC2** describes the **transition phase** between 20m and 40m, where the 20-30m and 30-40m split times are predominant (*time_30m_40m*, coefficient 0.498).
- **PC3** corresponds to the **reaction and initial acceleration phase**, centered on the 0-30m split times (*time_20m_30m*, coefficient 0.414).
- **PC4** incorporates **stride biomechanics and aerobic endurance** through stride amplitude (*stride amplitude*, coefficient 0.641) and VO_2max.
- **PC5** reveals **intermediate acceleration capacity**, dominated by acceleration between 10m and 20m (*acc_10m_20m*, coefficient 0.525).

The variables _30m_sprint with stop, time_20m_30m and time_30m_40m emerge as the best descriptors of 100m performance. They reflect the qualities of speed, explosiveness and transition, which are essential for differentiating Senegalese athletic profiles.

III-5-Clustering analysis with pre- and during-race variables correlated with 100m performance

III-5-1-K-Means Clustering (with the k-means algorithm)

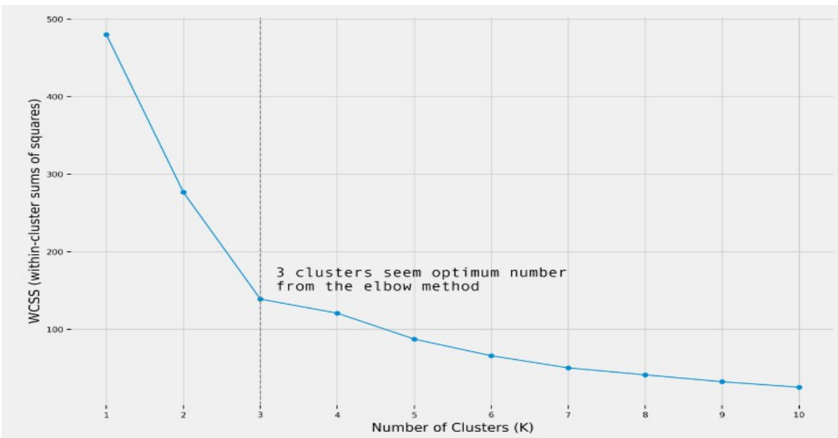

Figure 3. Graph describing the Elbow Method for determining the optimal number of clusters (K)

Interpretation: The Elbow Method indicates an optimal number of clusters equal to **3** with a minimum sum of squared errors (minimum intraclass variance) equal to **139.06**. The intraclass variance or inertia remains more or less high, which means that there are many differences between athletes who share the same cluster.

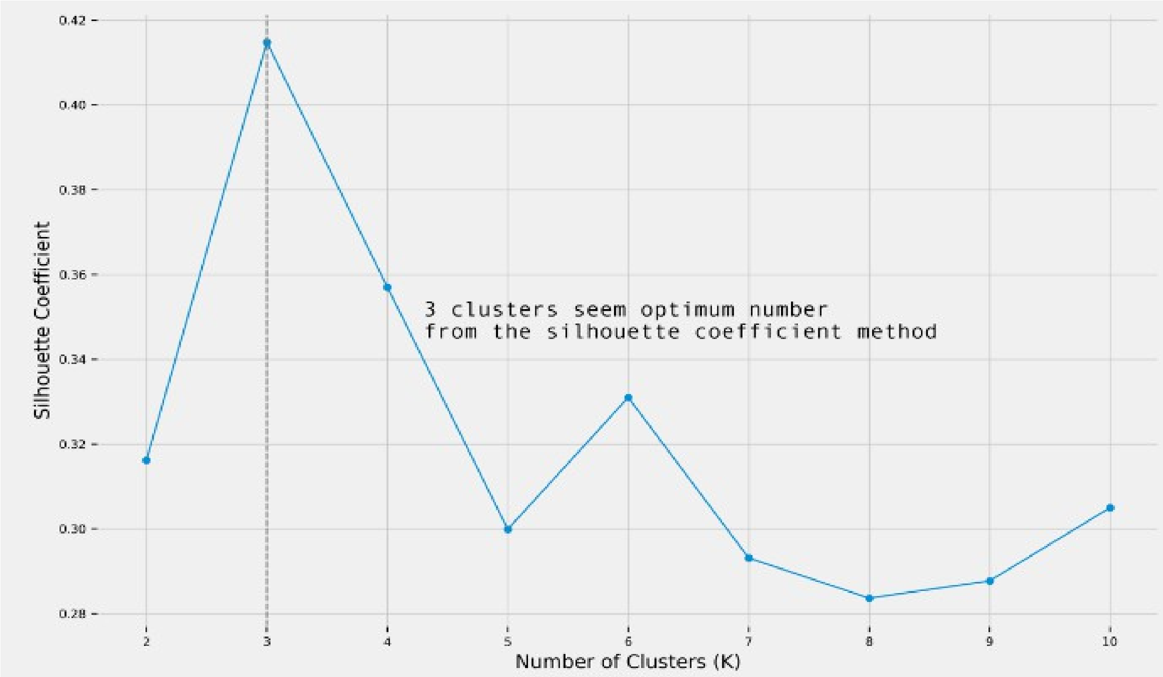

Figure 4. Graph describing the Silhouette Coefficient Method for determining an optimal number of clusters (K).

Interpretation: The **silhouette coefficient** method revealed an **optimal number of clusters equal to 3**, with a maximum value of **0.41**.

- This moderate score indicates that the separation between clusters is average.
- Some athletes are moderately well assigned to their cluster, but others are close to the boundaries, with a proximity comparable to the neighboring cluster.
- This suggests partial intra-cluster cohesion and relative inter-cluster differentiation, typical of groups with intermediate performance variations.

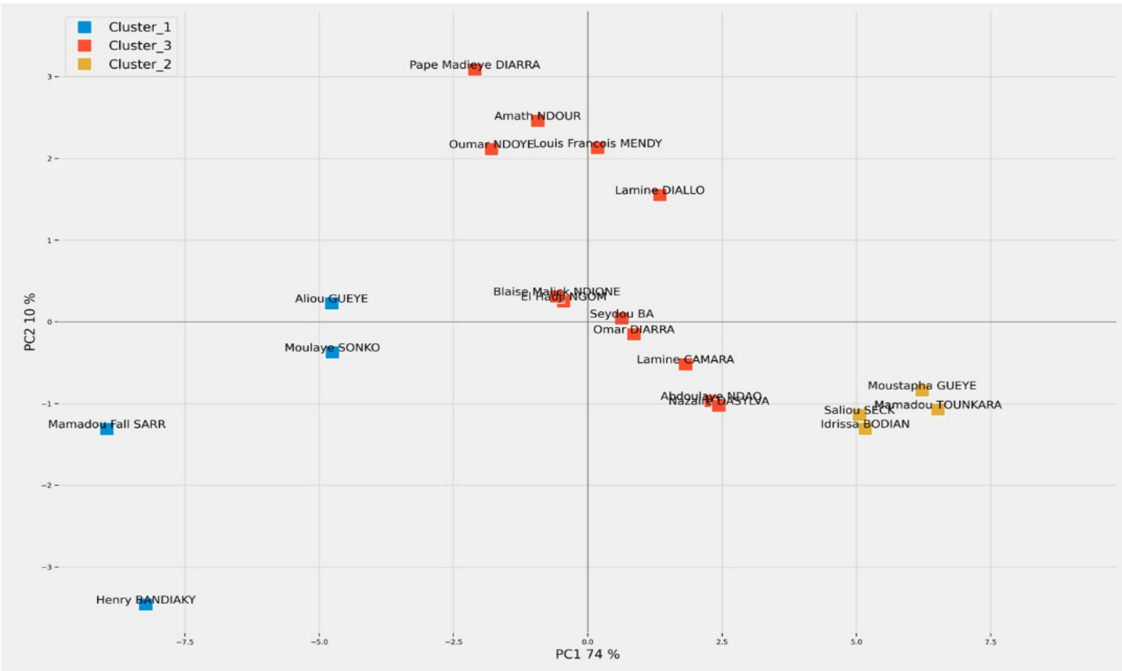

Figure 5. Projection of clusters formed by Senegalese athletes on the main axes of inertia PC1 and PC2 using the k-means algorithm.

Interpretation: According to this graph, the k-means algorithm has partitioned the Senegalese athletes into **three** more or less well-defined **clusters**, where each group of athletes is relatively more or less well separated from the others.

IV-5-2- Ward Clustering or Hierarchical Classification (using the top-down or divisive clustering approach)

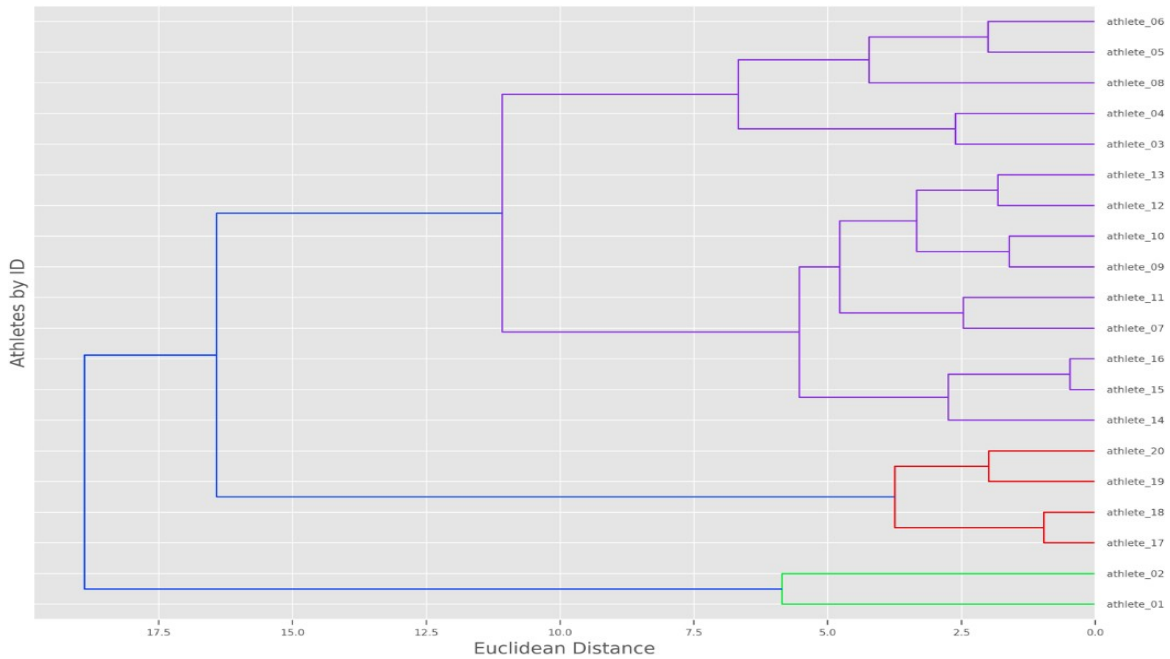

Figure 6 : Dendrogram describing the hierarchical clustering of Senegalese athletes using the Ward method.

Interpretation:

Ward's method using the top-down approach or divisive clustering cut at a Euclidean distance of 7.5 partitioned the Senegalese athletes into three well-separated clusters.

- **Cluster_1** is formed by athlete_01 and athlete_02;
- **Cluster_2** consists of athlete_17, athlete_18, athlete_19 and athlete_20;
- **Cluster_3** is composed of athlete_14, athlete_15, athlete_16, athlete_07, athlete_11, athlete_09, athlete_10, athlete_12, athlete_13, athlete_03, athlete_04, athlete_08, athlete_05 and athlete_06.

Unlike the K-Means method, Ward's method is more economical in correctly assigning athletes to the cluster to which they belong. In other words, Ward's method seeks to minimize the increase in intraclass variance to maximize interclass inertia in order to group the most similar athletes into one cluster and separate the most dissimilar athletes into different clusters.

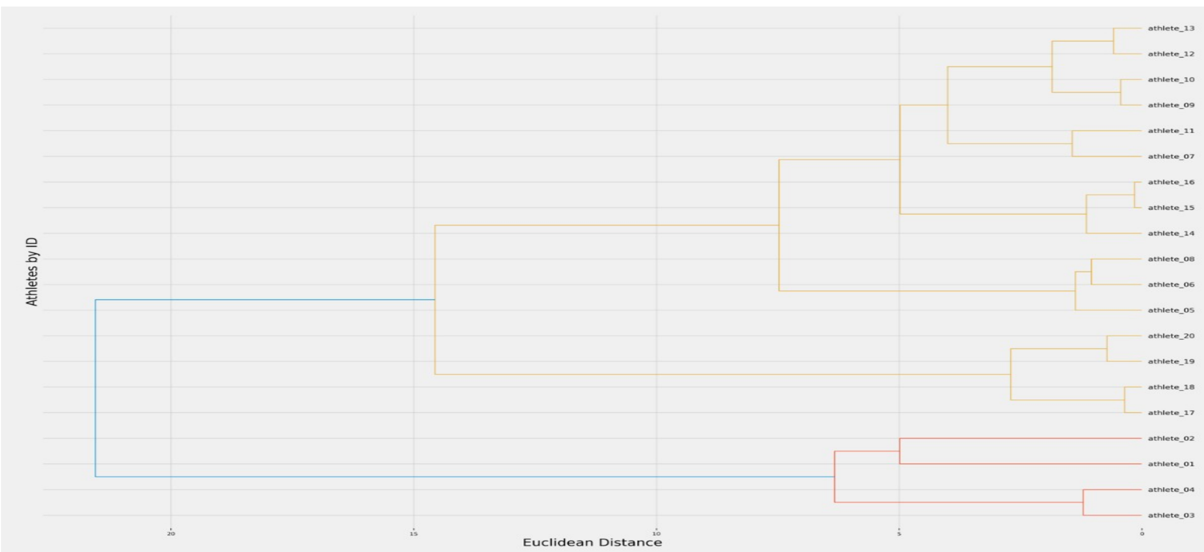

Figure 7. Dendrogram describing the hierarchical clustering of Senegalese athletes using Ward's method and constructed from principal component analysis (PCA) data

Interpretation: The two classification methods (Ward and K-Means) identified three similar clusters, with Cluster 2 remaining constant in both approaches. This indicates a high degree of homogeneity among the athletes in this group. On the other hand, Clusters 1 and 3 vary slightly, reflecting greater variability between the profiles of these athletes.

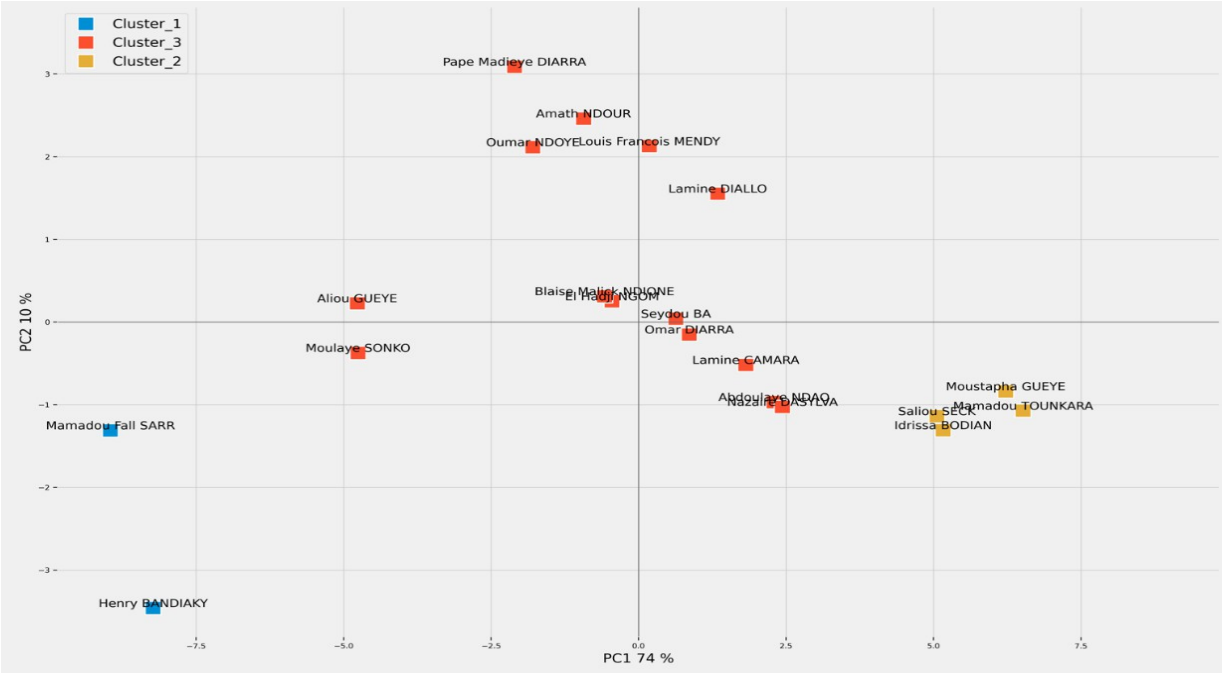

Figure 8. Projection of the clusters formed by Senegalese athletes on the main axes of inertia PC1 and PC2 using the Ward method

DISCUSSION

The results of this study confirm that several variables measured before and during the race show a significant correlation with performance in the 100m. In particular, speed over 30 meters from a standing start (r = 0.97) stands out as the most discriminating factor. This finding is consistent with the work of Morin and Samozino (1), who emphasize the importance of the strength-speed profile in the analysis of sprinting qualities. According to them, high initial speed reflects an optimal combination of maximum strength and power development, which is essential at the start and during the acceleration phase. The VO_2max variable (r = 0.59), traditionally associated with endurance disciplines, also showed a significant influence on performance. Although marginal in an effort as short as the 100m, it seems to play a role in recovery between efforts (repeated training sessions, qualifying phases) and potentially in maintaining a high level of performance over the last few meters.

This observation is consistent with the conclusions of Aguiar et al. (2), who emphasize the importance of aerobic capacity in limiting oxygen debt in high-level sprinters. Stride length, rather than stride frequency, emerged as a variable significantly correlated with performance. This result is consistent with the work of Weyand et al. (3), who demonstrate that stride length determines maximum speed more than the simple speed of leg movement.

This trend is particularly marked among the Senegalese sprinters in the sample, suggesting a prevalence of morphological profiles favorable to a large stride length (long segment lengths, favorable levers). Principal component analysis (PCA) reduced the complexity of the data while explaining 95.7% of the variance in performance through five synthetic components. Each component reflects a specific biomechanical or physiological dimension: movement speed (PC1), transition phase (PC2), initial acceleration (PC3), biomechanics and endurance (PC4), and intermediate acceleration (PC5). This hierarchical structure provides a better understanding of performance profiles and allows specific areas for improvement to be targeted for each athlete. In this sense, hierarchical classification (Ward) and K-Means clustering have identified three distinct sprinter profiles. These clusters could represent specific training groups:

- A very homogeneous group (Cluster 2), bringing together athletes with similar performances and similar physiological profiles;
- An elite group with low margins for improvement;
- An intermediate, more heterogeneous group, likely to benefit from targeted interventions.

This type of segmentation is recommended in the individualized training approach developed by Issurin (5), particularly in the context of block planning. Finally, the gap between the Senegalese sprinters analyzed and international standards reveals potential structural and genetic limitations. According to Claude Bouchard (4), differences in response to training are partly hereditary. Thus, beyond training, early identification of genetic potential could enrich talent detection and development programs in Senegal.

CONCLUSION

This multivariate study identified the key variables associated with 100m performance among Senegalese sprinters. Speed over 30m from a standing start, times achieved at the 20-30m and 30-40m splits, and VO2max are the most predictive. ACP and clustering were used to effectively model the performance structure. These results open up new possibilities for talent detection, individualized training and international comparison.

REFERENCES

1. Morin JB, Samozino P. Interpreting power-force-velocity profiles for individualised and specific training. Int J Sports Physiol Perform. 2016;11(2):267–72.
2. Aguiar R, et al. Maximal accumulated oxygen deficit and performance in sprint. J Sci Med Sport. 2015;18(2):211–5.
3. Weyand PG, et al. Faster top running speeds are achieved with greater ground forces not more rapid leg movements. J Appl Physiol. 2000;89(5):1991–9.
4. Bouchard C. Genomic predictors of trainability. Exp Physiol. 2012;97(3):347–52.
5. Issurin VB. Benefits and limitations of block periodised training. Sports Med. 2008;38(8):579–605.

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