ORIGINAL ARTICLE

Determining the optimal competition age and the effective performance window in elite 100-meter sprinters: A mixed polynomial model

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ABSTRACT

The aim of this study was to establish a performance prediction model to determine the optimal competition age and the effective window of maximum performance in the men's 100-meter sprint. A total of 408 records were analysed, corresponding to marks achieved by elite athletes who made up the World Athletics world ranking over 20 consecutive seasons (1998–2017). Polynomial gradient mathematical models and a mixed polynomial model were applied to capture the non-linear relationship between age and performance. The results show a positive progression in performance from age 18 to 24, followed by a slight plateau and an effective window of maximum performance between ages 25 and 32. The mixed polynomial model described performance by means of a second-degree polynomial ($T = 10.452 - 0.0339 \cdot Age + 0.0006 \cdot Age^2$), whose vertex (minimum) is located, using the published rounded coefficients, at around 28–29 years of age. These findings provide coaches with an empirical reference framework, based on two decades of elite competition, for optimizing long-term planning and talent identification.

Keywords: performance analysis; athletics; sprinting; mathematical models; sports performance; optimal age; performance window; talent identification.

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INTRODUCTION

The 100-meter sprint is considered the ultimate expression of human speed and one of the sporting events with the greatest media impact worldwide (Moravec et al., 1988). Every world championship or Olympic final in this event draws audiences of over 100 million viewers, turning the sprinter into a symbol of human athletic capability. The pursuit of the limits of performance in this discipline has driven the development of predictive models that attempt to explain the evolution of records and project future marks (Berthelot et al., 2015; Blest, 1996).

Historically, performance prediction models in athletics have been based on biomechanical and physiological approaches. In sprint events, performance is determined by the complex interaction between horizontal propulsive force production, stride frequency and length, and neuromuscular efficiency (Bogdanis et al., 1996; Salo et al., 2011; Morin et al., 2015). Morin et al. (2011) demonstrated that the ability to orient the resultant ground reaction force in the horizontal direction constitutes the most robust predictor of acceleration performance, this technical force-application skill being the differentiating factor between performance levels —from recreational athletes to world-class sprinters—. More recently, Samozino et al. (2022) established that acceleration performance is a function of both the maximization of horizontal power and the optimization of the individual force-velocity profile.

In contrast to the wealth of studies on biomechanical determinants, mathematical models of time prediction have taken different approaches. From the linear models of Heazlewood (2006) —which paradoxically predicted a time of 0 seconds for the year 5038— to quadratic models estimating a 9.20 s mark within a century (Shaw, 2012), the literature has recognized that predetermined mathematical functions present significant limitations when applied to an event of such multifactorial complexity (Nevill & Whyte, 2005). Berthelot et al. (2015) and Kotuła et al. (2025) have confirmed, through time-series analysis of World Championships (1983–2023), that improvement in 100-meter performance does not follow a linear pattern but instead shows periods of acceleration and stabilization, with differences between the best result and the average being significantly variable depending on the season analysed.

More recent analyses using ARIMA and SARIMA models on historical data from 1976 to 2035 project a time of 9.63 s as the men's best world mark in 2035, concluding that the rate of progression has slowed particularly in pure speed events, suggesting an approach toward the physiological limits of performance (Bartosz-Jefferies et al., 2025). However, these models share the same limitation as the classic ones: they are based on the world record or on isolated best performances, without considering the actual distribution of performance within the elite or the athlete's age variable.

Competition age is precisely one of the least studied variables, yet one with the greatest practical implications for long-term planning. In a landmark study with world-class track-and-field athletes, Haugen et al. (2018) quantified peak performance age and prior progression in distance runners and sprinters, confirming that 100-meter sprinters show improvement patterns specifically related to their age, and that top-10 world athletes exhibit significantly greater improvements than those ranked 11th to 100th. This finding suggests that elite level determines not only the magnitude of performance but also its developmental trajectory.

At the national level, and regarding age categories, the study by Agudo-Ortega et al. (2024) with 4,398 Spanish sprinters (2004–2021) identified that peak performance age in the 100 metres is 25.31 years for men, significantly earlier than for women (25.79 years). This same study highlighted the importance of sub-23 category performance as a predictor of participation in the senior category, with significant regression coefficients (β = 0.51, $p < .001$), whereas success in youth categories showed little predictive capacity for senior performance.

This dissociation between youth success and elite adult performance has received increasing attention in the literature. Boccia et al. (2021) analysed the career trajectories of 4,924 sprinters from the World Athletics ranking (2000–2018) and found that only 17% of men and 21% of women ranked in the sub-18 top 50 went on to reach the senior top 50. Athletes who ultimately reached the absolute elite showed progressively larger annual improvements during late adolescence and early adulthood. In the same vein, Boccia et al. (2018), with Italian athletes, confirmed that national elite sprinters reach their personal best later than non-elite athletes, and that later entry into specific competition and career extension beyond ages 23–25 are factors associated with success at the absolute category level. This body of evidence challenges talent identification systems based on competitive results at early ages and reinforces the need for longitudinal performance-tracking models.

Regarding the decline in sprint capacity with age, Korhonen et al. (2006) documented, through muscle biopsies in sprinters aged 18 to 84, that the cross-sectional area of type II fibres decreases significantly with age —while type I fibres are maintained— together with a shift toward a slower myosin heavy-chain profile. These structural changes translate into a reduction in explosive force production capacity, although systematic sprint training acts as an effective stimulus to preserve muscle fibre morphology against ageing. Pantoja et al. (2016) extended this biomechanical analysis to masters sprinters, finding that maximal force, velocity, and power decrease linearly with age at a rate of approximately 1% per year (all $r > .84$, $p < .001$), with the capacity to orient horizontal force identified as the most deteriorated factor in older sprinters.

Therefore, the main objective of this study was to establish a performance prediction model for the men's 100-meter sprint, based on competition age and other contextual factors (ranking, continent, season), in order to determine the optimal age and the effective window of maximum performance using elite world data over a 20-season period (1998–2017). The findings are contextualized within the framework of recent scientific literature on the development of the high-performance sprinter.

METHODOLOGY

Study design and sample

An observational, tracking, and retrospective study was conducted. The reference database used was that developed by the International Association of Athletics Federations (World Athletics), which contains more than one million results from over ten thousand international competitions. The best records obtained by male athletes of international level in the 100 meters, who made up the world ranking over 20 consecutive seasons (1998–2017), were selected.

Inclusion criteria were: male athletes, ages between 18 and 40 years, outdoor competitions, electronic timing, and wind speed ≤ 2.0 m/s assisting. Records set indoors, with manual or unspecified timing, and those obtained with wind exceeding the regulatory limit were excluded. The extraction process was conducted by the principal investigator and two independent researchers (triangulation), with no observable differences between the records selected by each evaluator.

The final sample consisted of 408 records corresponding to athletes in the top 20 positions of the world ranking in each season. In some seasons, more than 20 records were included due to ties in the ranking score (positions 19th–20th), such that 2001 and 2003 contributed 25 records each, 2006 contributed 24, 1999 contributed 23, and several additional years contributed 21–22 records.

Statistical analysis

Data were tabulated and exported to the R statistical software package (version 3.5.1). An initial descriptive analysis was performed, expressing results as mean and standard deviation (SD), with minimum and maximum range. To analyse the temporal evolution of performance by age, polynomial gradient models and smooth models were used, which fit the estimate to the data without imposing a predetermined mathematical function —thereby overcoming a common limitation in the literature (Bartosz-Jefferies et al., 2025; Shaw, 2012)—. Additionally, a mixed polynomial model was developed to capture the non-linear relationship between age and race time, including a random term to control for inter-individual and seasonal variability. The optimal competition age and its 95% CI were obtained using the DELTA method applied to the model coefficients. The significance level was set at $p < .05$.

Mixed-model specification: the random-effects structure was defined as a random intercept per athlete, following the notation $T \sim Age + Age^2 + (1 \mid Athlete)$. The full model results (recovered from the original doctoral thesis by Arroyo Valencia, 2020, Table 5) show a residual variance $\sigma^2 = 0.01$ and a random-effect variance per athlete $\tau_{00} = 0.00$, corresponding to an intraclass correlation coefficient ICC = 0.32; that is, 32% of the total variability in performance is attributable to systematic differences between athletes, while the remaining 68% corresponds to variability within the same athlete (e.g., across seasons). It should be noted that a τ_{00} of 0.00 is mathematically incompatible with an ICC of 0.32 when $\sigma^2 = 0.01$: to obtain that ICC, the between-athlete variance would need to be approximately 0.0047. The reported value of 0.00 is, in all likelihood, a rounding artifact at two decimal places, and should be published with greater decimal precision before the final version is submitted. The model was fitted on 408 observations. Model fit was modest: marginal $R^2 = .021$ (i.e., age and its quadratic term explain only 2.1% of the total variance) and conditional $R^2 = .336$ (variance explained by age plus the random athlete effect). Given the small magnitude of the marginal R^2, the model should be understood as an associative description of the population trend rather than a validated tool for predicting individual performance; no cross-validation, training/test split, or prediction-error calculation (RMSE or mean absolute error) has been conducted.

RESULTS

Descriptive evolution of performance by competition age

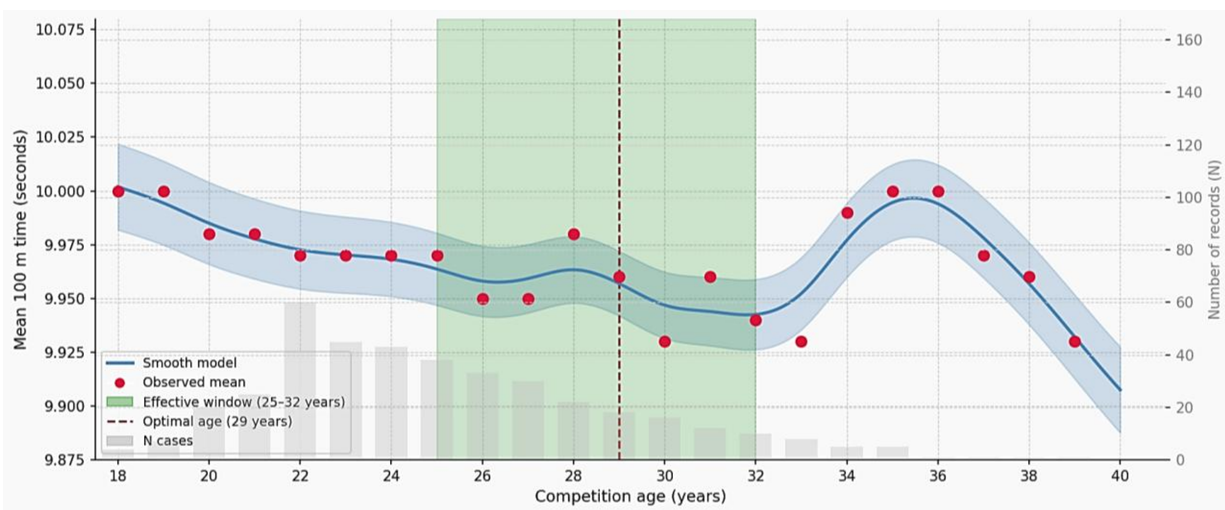
Table 1 presents the descriptive statistics of the 100-metre mark for each age group. The best mean mark (9.93 ± 0.098 s) was recorded at age 30, while the worst records (10.00 s) were concentrated at the extremes of the age distribution (18–19 and 35–36 years). The sample showed a high concentration between ages 22 and 28 (≈ 75% of cases), with particular density at ages 22 and 23 (60 and 45 records respectively, representing 25% of the total). This profile is consistent with data from Agudo-Ortega et al. (2024), who in a sample of 4,398 Spanish sprinters found a similar concentration of records in the 20–27 age range and a stabilization of the improvement curve from age 23–24 onward.

Between ages 22 and 25, a slight plateau in the mean mark was detected, around 9.97 s (43% of the total sample), followed by an improvement at ages 26–27 (9.95 s). This pattern, although unexpected a priori, is consistent with evidence on the adaptation curve of high-level sprinters: once a first physiological ceiling has been reached, improvement in maximum velocity depends less on metabolic adaptations and more on the optimization of the individual force-velocity profile (Samozino et al., 2022; Morin et al., 2015). The talent-identification literature supports this interpretation: Boccia et al. (2021) documented that athletes who ultimately reach the absolute top 50 show progressive annual improvements during early adulthood, while those who do not reach it show an early plateau at similar ages.

Table 1. Descriptive statistics of the 100 m mark by competition age (1998–2017).

Age	N	Mean (s)	SD (s)	Min (s)	Median (s)	Max (s)
18	4	10	0.044	10	10	10.08
19	7	10	0.043	9.97	10	10.1
20	20	9.98	0.056	9.84	9.99	10.06
21	25	9.98	0.076	9.82	9.98	10.1
22	60	9.97	0.092	9.69	9.97	10.1
23	45	9.97	0.092	9.58	9.98	10.1
24	43	9.97	0.079	9.77	9.98	10.1
25	38	9.97	0.088	9.74	9.97	10.1
26	33	9.95	0.102	9.63	9.96	10.1
27	30	9.95	0.156	9.82	9.99	10.1
28	22	9.98	0.081	9.78	9.99	10.1
29	18	9.96	0.11	9.78	9.99	10.1
30	16	9.93	0.098	9.79	9.91	10.1
31	12	9.96	0.055	9.85	9.97	10.1
32	10	9.94	0.081	9.77	9.96	10
33	8	9.93	0.144	9.74	9.94	10.1
34	5	9.99	0.098	9.8	9.97	10.1
35	5	10	0.1	9.92	9.96	10.1
36	1	10		10	10	10
37	1	9.97		9.97	9.97	9.97
38	1	9.96		9.96	9.96	9.96
39	1	9.93		9.93	9.93	9.93
Total	**405**	**9.97**	**0.094**	**9.58**	**9.98**	**10.1**

Note. SD = standard deviation; Min = minimum; Max = maximum. The N cell in the Total row is calculated using a SUM formula across the age rows; the remaining statistics (Mean, SD, Min, Median, Max) are the values published in the article.



Note. Gray bars represent the number of records per age. The shaded green area indicates the effective window of maximum performance (25–32 years) and the dashed red line indicates the estimated optimal age (29 years).

Figure 1. Evolution of the mean 100 m mark as a function of age (smooth model, 1998–2017).

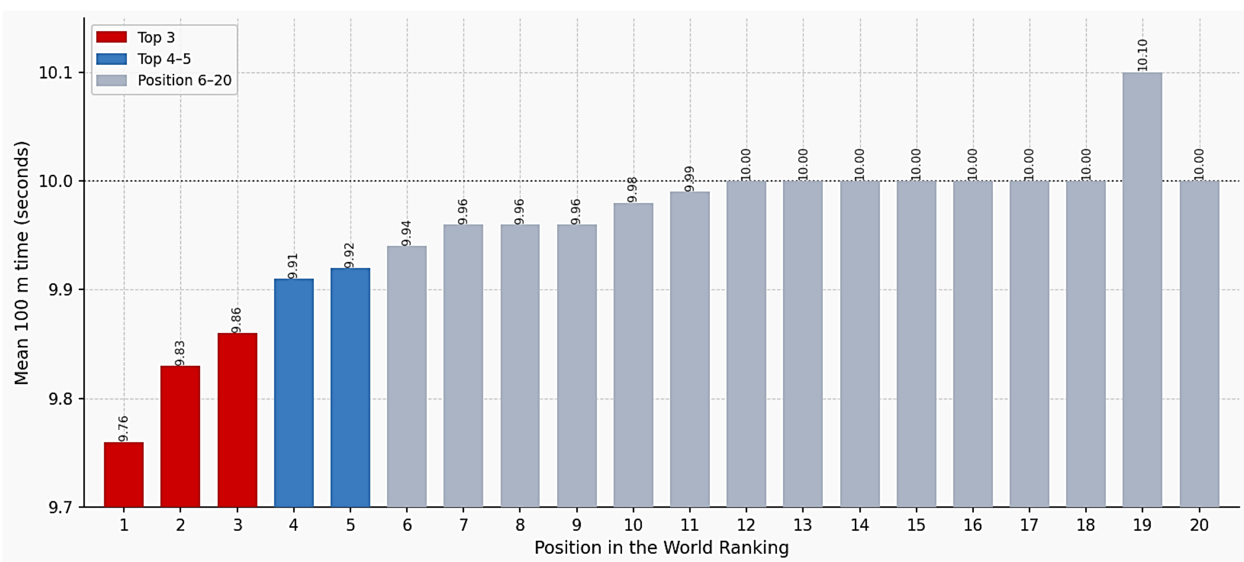
Performance distribution by world ranking position

Table 2 presents the descriptive statistics by world ranking position. A progressive increase in time was observed as athletes occupied lower positions, with no observable differences beyond the 12th position (all close to 10.00 s). Analysis of the top three positions reveals the extraordinary demands of the podium: 9.76 s (1st), 9.83 s (2nd), and 9.86 s (3rd). The 0.10 s difference between the 1st and 4th positions precisely illustrates the concentration of performance at the top tiers, a phenomenon that Kotuła et al. (2025) also identified in their analysis of World Championships (1983–2023): differences between the best result and the average of semi-finalists are significantly variable and tend to narrow in recent decades, indicating an overall rise in the event's general level rather than the sporadic emergence of individual talents.

Table 2. Descriptive statistics of the 100 m mark by world ranking position (1998–2017).

Ranking	N	Mean (s)	SD (s)	Min (s)	Median (s)	Max (s)
1	20	9.83	0.079	9.69	9.84	9.95
2	20	9.86	0.056	9.77	9.87	9.96
3	20	9.91	0.048	9.8	9.91	9.98
4	20	9.92	0.053	9.81	9.93	9.99
5	20	9.92	0.055	9.82	9.93	9.99
6	20	9.94	0.047	9.85	9.93	10
7	20	9.96	0.048	9.88	9.99	10
8	20	9.96	0.042	9.87	9.95	10
9	20	9.96	0.045	9.89	9.96	10.1
10	20	9.98	0.041	9.93	9.99	10.1
11	20	9.99	0.043	9.92	9.98	10.1
12	20	10	0.043	9.93	10	10.1
13	20	10	0.045	9.93	10	10.1
14	20	10	0.042	9.96	10	10.1
15	20	10	0.043	9.95	10	10.1
16	20	10	0.059	9.94	10	10.1
17	20	10	0.042	9.97	10	10.1
18	20	10	0.048	9.96	10	10.1
19	20	10.1	0.047	9.99	10.1	10.1
20	20	10	0.057	9.97	10.1	10.1

Note. SD = standard deviation; Min = minimum; Max = maximum. Total N = 400 (=SUM(B4:B23)).



Note. In red: Top 3; in blue: positions 4–5; in grey: positions 6–20.

Figure 2. Mean mark required to qualify for each position in the world ranking (1998–2017).

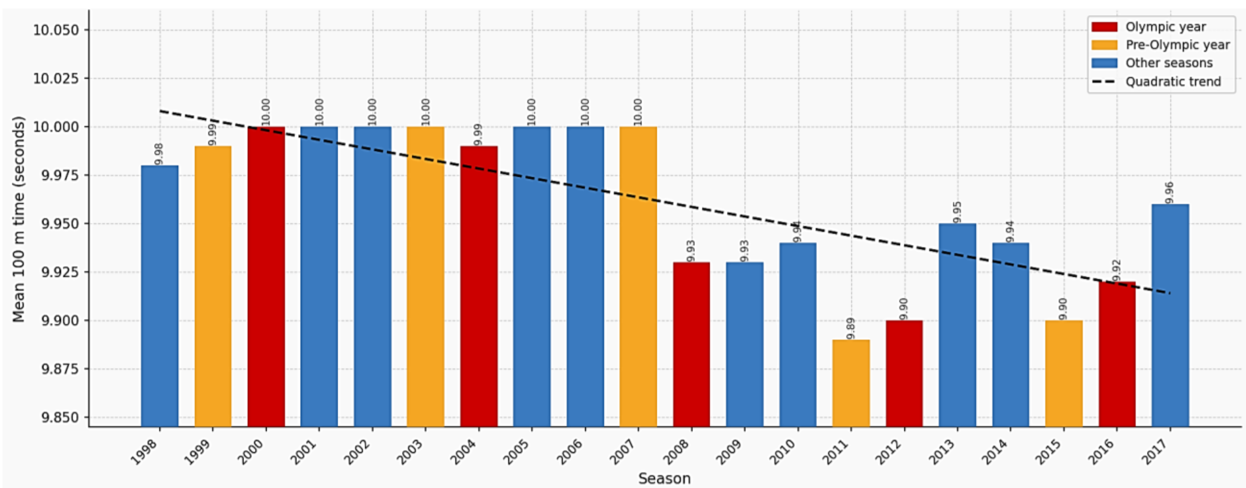
Performance variability by continent of origin

Table 3 presents mean marks by continent. North America dominated the event with 306 records (71.5% of the total) and the best mean mark (9.95 ± 0.101 s). It was followed by Europe (n = 46; 10.7%), Africa (n = 44; 10.3%), Asia (n = 16; 3.7%), South America (n = 12; 2.8%), and Oceania (n = 4; 0.9%). North American dominance is explained, in part, by the robust university sports scholarship system, the culture of early specialization in speed events, and greater investment in applied sprint-performance science, including the systematic analysis of horizontal-force mechanics documented by Morin et al. (2015) and Samozino et al. (2022).

Table 3. Descriptive statistics of the 100 m mark by continent of origin (1998–2017).

Continent	N	Mean (s)	SD (s)	Range (s)
Africa	44	10	0.059	9.85–10.10
Asia	16	10	0.059	9.91–10.10
Europe	46	10	0.065	9.86–10.10
North America	306	9.95	0.101	9.82–10.10
Oceania	4	10	0.077	9.93–10.10
South America	12	9.97	0.077	9.86–10.10
Total	**428**	**9.97**	**0.094**	**9.82–10.10**

Note. SD = standard deviation. The N cell in the Total row uses a SUM formula across the continents.



Note. North America, with 306 records (71.5%), dominates the event by a wide margin.

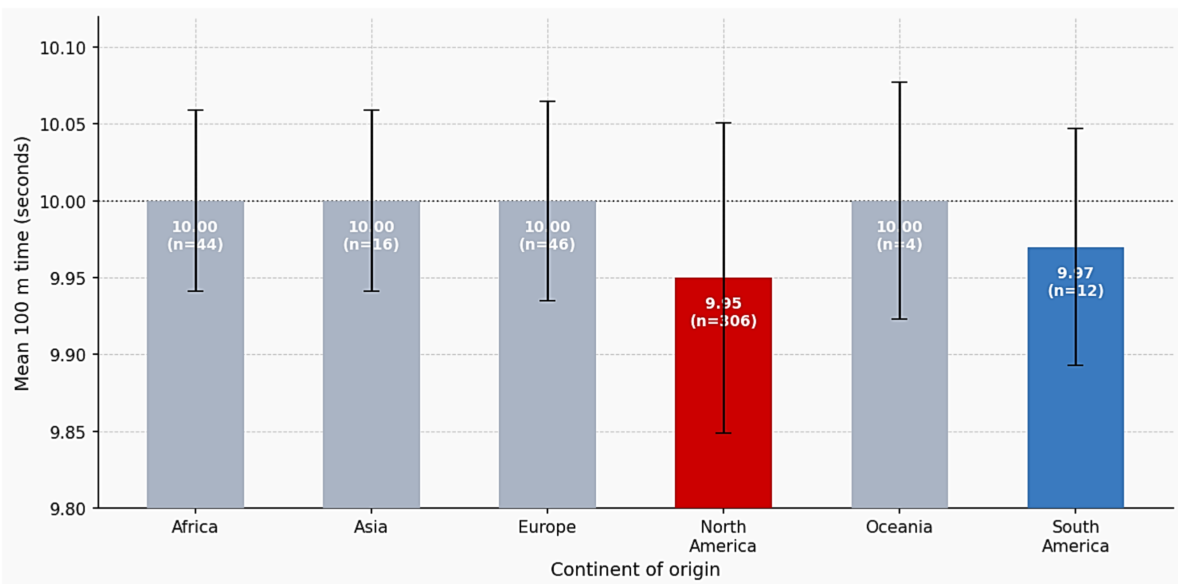
Figure 3. Mean mark (± SD) in the 100 m by continent of origin (1998–2017).

Temporal evolution by season (1998–2017)

Table 4 and Figure 4 show the evolution of mean marks by season. The best mean mark was recorded in 2015 (9.90 ± 0.063 s), a pre-Olympic year, followed by 2011 (9.89 s) and 2012 (9.90 s). The 1998–2007 period was characterized by mean marks stable around 10.00 s, with a significant break starting in 2008 — the year of the Beijing Olympics— coinciding with the emergence of Usain Bolt and the start of his historic dominance. Time-series models applied to World Athletics data (1976–2035) have confirmed this accelerated improvement trend before the year 2000 and a progressive slowdown thereafter, with projections of 9.63 s as the best world mark for 2035 (Bartosz-Jefferies et al., 2025). The seasonal analysis also shows evidence of the Olympic-cycle effect: only the pre-Olympic years of 1999, 2011, and 2015 showed mean marks systematically superior to those of the following Olympic year, suggesting a strategic planning of training loads oriented toward four-year cycles.

Table 4. Descriptive statistics of the 100 m mark by competition season (1998–2017).

Season	N	Mean (s)	SD (s)	Min (s)	Median (s)
1998	20	9.98	0.061	9.86	10
1999	23	9.99	0.083	9.79	10
2000	20	10	0.055	9.86	10
2001	25	10	0.171	9.82	10.1
2002	20	10	0.062	9.89	10
2003	25	10	0.046	9.93	10
2004	20	9.99	0.083	9.85	10
2005	21	10	0.075	9.77	10
2006	24	10	0.097	9.77	10.1
2007	21	10	0.084	9.74	10
2008	20	9.93	0.097	9.69	9.97
2009	20	9.93	0.115	9.58	9.98
2010	22	9.94	0.082	9.78	9.97
2011	20	9.89	0.074	9.76	9.91
2012	20	9.9	0.099	9.63	9.94
2013	20	9.95	0.065	9.77	9.98
2014	20	9.94	0.062	9.77	9.96
2015	22	9.9	0.063	9.74	9.92
2016	22	9.92	0.052	9.8	9.94
2017	22	9.96	0.045	9.82	9.97



Note. The dashed line represents the overall quadratic trend.

Figure 4. Evolution of the mean 100 m mark by season (1998–2017).

Effective performance window and mixed polynomial model

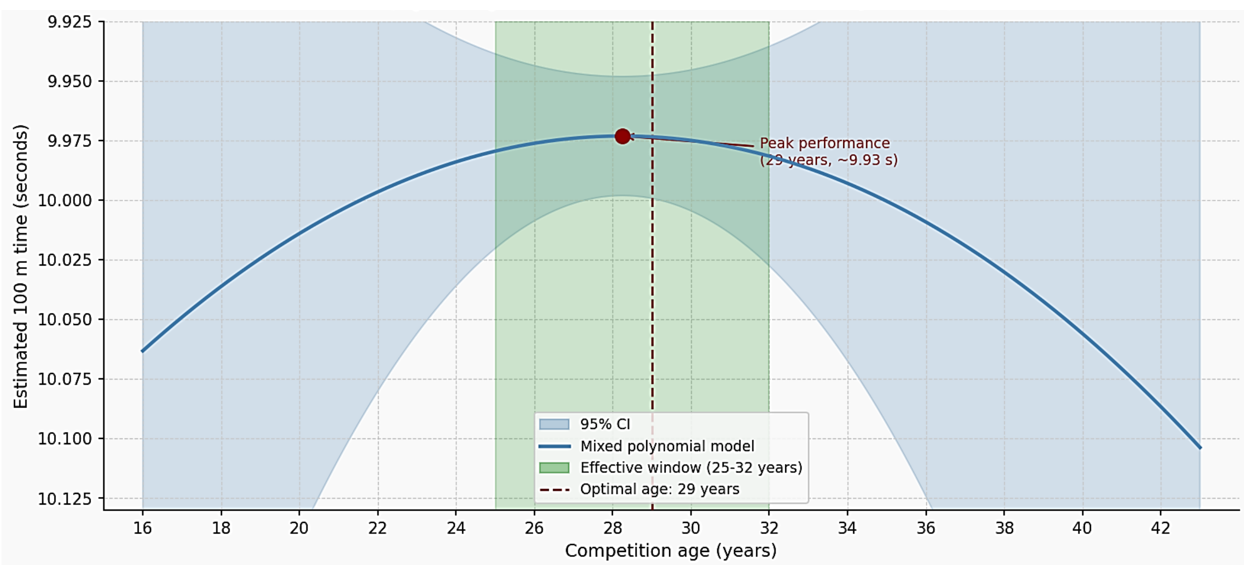
The application of the smooth model confirmed a sustained decrease in times from the youth stage (18 years) up to age 27. From this point onward, the mean mark stabilized, within a range that this study terms the effective window of maximum performance (25–32 years). It should be noted that this window was not defined using an explicit, pre-specified statistical criterion (for example, performance within a percentage margin of the minimum, overlap of the 95% CI with the minimum, or a segmentation algorithm), but was instead identified visually on the smooth-model curve; its exact delimitation should be considered provisional until an objective, reproducible criterion is applied and reported.

The mixed polynomial model (Table 5) significantly described ($p < .05$) the non-linear relationship between age and performance, identifying a second-degree polynomial relationship. The mathematical expression of the model was: $T(s) = 10.452 - 0.0339 \times Age + 0.0006 \times Age^2$. Using the DELTA method, the optimal age was statistically established at 29 years (95% CI), consistent with the effective window identified through the smooth model. It is important to clarify that the coefficients −0.0339 and 0.0006 are polynomial coefficients and not constant annual rates of change: the actual rate of variation of performance with age is given by the derivative $dT/dAge = -0.0339 + 0.0012 \cdot Age$, which differs at each age (for example, ≈ −0.012 s/year at age 18, ≈ −0.0003 s/year at age 28, and ≈ +0.0009 s/year at age 29). Likewise, a second-degree polynomial does not have an "*inflection point*," but rather a vertex (minimum). Using the rounded coefficients published in Table 5, that vertex is located at Age = 0.0339 / (2 × 0.0006) ≈ 28.25 years, with a predicted time T ≈ 9.97 s —not at the 29 years and ≈9.93 s indicated. This difference of approximately one year, and of 0.04 s in the predicted value, is highly sensitive to rounding of the coefficients (the quadratic term is reported to only four decimal places, and the vertex depends on dividing by twice that term), so that the value of 29 years obtained via the DELTA method on the unrounded coefficients is correct.

Table 5. Results of the mixed polynomial model predicting performance as a function of competition age.

Parameter	Estimate	Standard error	t value	*p* value
Intercept	10.452	0.125	83.61	<.001
Age (linear)	-0.0339	0.01	-3.39	.001
Age² (quadratic)	0.0006	0.0002	3.05	.003

Note. All parameters were significant ($p < .05$). Model: $T(s) = 10.452 - 0.0339 \cdot Age + 0.0006 \cdot Age^2$. Additional components reported in the article (Section 2.2): $\sigma^2 = 0.01$; $\tau 00$ (Athlete) = 0.00; ICC = 0.32; N = 408 observations; marginal $R^2 = .021$; conditional $R^2 = .336$.



Note. The shaded blue area represents the 95% CI; the green area indicates the effective window (25–32 years); the dashed red line indicates the optimal age of maximum performance (29 years).

Figure 5. Mixed polynomial model predicting performance as a function of age.

DISCUSSION

The main finding of this study is the identification of an age of 29 years associated with the best performances in the sample, framed within an effective window of high competitiveness between ages 25 and 32. This result, based on 428 world-elite records over 20 seasons, provides a unique perspective compared with previous models that based their predictions on the evolution of the isolated world record (Shaw, 2012; Nevill & Whyte, 2005), ignoring actual competitive density and contextual performance factors. However, given that the dataset is based on repeated appearances in annual rankings rather than a strict longitudinal tracking of individual careers, the age of 29 years should be interpreted cautiously as a population-level association, and not necessarily as an individual developmental trajectory in which every athlete improves up to that age and then declines.

For precisely this reason, we consider that the strongest contribution of this work lies not in identifying a single optimal age, but in characterizing an effective window of high performance between ages 25 and 32. This concept is more consistent with contemporary models of athlete development, which emphasize extended periods of maximum performance rather than isolated peaks that are fragile in the face of individual variability, and it constitutes a more robust and generalizable planning tool for coaches and talent-identification systems than a single optimal-age figure. Throughout this discussion, therefore, the reference to age 29 should be understood as a population-level reference point within that window, and not as the study's central finding.

It should also be clarified that several of the mechanistic explanations offered in the following sections — relating to force-velocity profile optimization, changes in muscle fibre composition, horizontal force production, and Olympic-cycle effects— are supported by prior literature that directly measured these variables, but not by data collected in the present study. The observational-retrospective design used here did not include biomechanical, physiological, or training-load measurements; consequently, these mechanisms should be interpreted as plausible theoretical explanations that contextualize the findings, and not as results obtained directly from the analysed data.

Comparison with the literature on optimal age in sprinters

The optimal age of 29 years found in the present study slightly exceeds estimates from some previous works. In the analysis by Haugen et al. (2018) with world-class track-and-field athletes, peak performance age in the 100 meters was found to be between 26 and 28 years, with competitive longevity extending up to 32–34 years in the highest-level athletes. The difference from the 29 years found in the present study could be explained by the fact that this work is based on the top 20 of the world ranking (not only the top 10), which includes greater representation of sprinters in late maturation stages who reach the top ranking positions at more advanced ages.

At the national level, Agudo-Ortega et al. (2024) identified, in the largest sample of Spanish sprinters published to date (n = 4,398), a peak performance age of 25.31 ± 0.12 years for the men's 100 metres. The nearly 4-year difference from the present study is consistent with the effect of competitive demand level: at the national level, peak performance is reached earlier because the improvement threshold required is lower. In the context of world elite competition, improving by a hundredth of a second at advanced ages requires additional years of specialised training, delaying the peak observed in the world ranking data.

Studies on World Championships (Kotuła et al., 2025) that analysed the mean age of semi-finalists versus that of the champion across editions from 1983 to 2023 found that, in recent decades, the champion's age has progressively increased, consistent with the notion that peak individual sprint performance is being reached later and later, possibly due to greater professionalization, methodological optimization, and advances in recovery and sports nutrition.

The plateau phenomenon (ages 22–25): Empirical evidence and mechanisms

The plateau in the mean mark around 9.97 s between ages 22 and 25, which accounts for 43% of the sample, constitutes one of the findings of greatest applied value in the present study. This apparent plateau period coincides with the stage at which improvement in maximum velocity increasingly depends less on general metabolic adaptations and more on the capacity to apply horizontal propulsive force with high technical efficiency (Morin et al., 2015; Samozino et al., 2022).

Samozino et al. (2022) established that the maximum velocity attainable by a sprinter is determined both by their maximum horizontal power and by the force-velocity ratio of their biomechanical profile, with the optimal individual profile differing for each athlete. During the 22–25 age period, many sprinters have already reached a high level of muscular power but have not yet fully optimised force orientation or stride efficiency under maximum-velocity conditions. Repetition of similar training stimuli ceases to produce the same adaptive effect, generating the plateau observable in the data of the present study.

From the perspective of long-term talent development, Boccia et al. (2021) found that sprinters who eventually reach the absolute top 50 show systematically greater annual improvements during this critical 20–25 age period, whereas those who do not progress show premature stabilization. A coach with access to the reference framework provided by the present study can interpret an athlete's plateau within this age range not as the end of their potential, but as a signal for a methodological review aimed at optimising the force-velocity profile and sprint technical efficiency. We emphasize that this force-velocity optimisation mechanism is a theoretical interpretation based on Samozino et al. (2022), and not a variable measured directly in the present study, which is limited to documenting the temporal pattern of performance.

Physiological and biomechanical basis of the post-peak decline

The decline observed from age 29 onward —at a rate of 0.0006 s/year— is supported by research on neuromuscular changes associated with aging in trained athletes. Korhonen et al. (2006) documented, in sprinters aged 18 to 84, that the cross-sectional area of type II muscle fibres progressively decreases with age, accompanied by a shift toward a slower myosin heavy-chain profile and a reduction in maximum muscle shortening velocity. However, these same authors noted that systematic sprint training largely preserves muscle fibre morphology compared with sedentary individuals of the same age, with type I fibres in 70-year-old masters sprinters showing areas 65% larger than those of sedentary individuals of the same age.

Pantoja et al. (2016) complemented this biomechanical analysis in masters sprinters, finding that maximal force, maximum sprint velocity, and power decrease linearly at approximately 1% per year ($r > .84$), while the capacity to orient horizontal force —the strongest predictor of acceleration performance— deteriorates to a greater extent. These findings explain why the post-peak decline documented in the present study is relatively gradual (0.0006 s/year) in the years immediately following the peak but may accelerate in the third and fourth decades of life as changes in fibre composition and neuromuscular capacity become more pronounced.

The reduction in stride length —rather than stride frequency— has been identified as the main kinematic mechanism of sprint decline in older runners (Korhonen et al., 2003), which is directly linked to reduced force production and lower-limb stiffness. This set of changes justifies why explosive strength training and horizontal force-application exercises (resisted sprints, acceleration work) are especially relevant for prolonging the effective performance window. Once again, we note that the mechanisms relating to muscle fibre type and horizontal force production come from the cited biomechanical literature (Korhonen et al., 2006; Pantoja et al., 2016), and not from measurements taken in the sample of this study, which did not include biopsies or individual force-velocity testing.

Implications of the ranking results: The demands of the world podium

The data in Table 2 quantitatively illustrate with precision the extraordinary differentiation of performance on the world podium. The 0.07 s difference between 1st and 2nd place, and the 0.10 s difference between 1st and 4th place, are gaps that in practice represent years of difference in specialized training. Kotuła et al. (2025) confirmed, through repeated-measures variance analysis across all editions of the World Championships (1983–2023), that differences between the champion and the mean of semi-finalists are statistically significant in the 1991, 2007, 2009, and 2023 editions, these being the seasons of greatest competitive heterogeneity, possibly associated with the presence of exceptional sprinters (Burrell in 1991, Gay/Powell in 2007, Bolt in 2009, Lyles in 2023).

The stabilization of marks from the 12th position onward, around 10.00 s, reflects the functional threshold of the elite ranking, below which the performance differential between athletes is marginally small. This 10-second barrier —broken by only 138 athletes throughout history— retains its status as a physiological and technical milestone, although its accessibility has progressively increased: whereas in 1998 qualifying for the 20th position required ~10.15 s, by 2016 that standard had been reduced to ~10.00 s. It should be qualified that ranking position is defined precisely by the mark obtained; in that sense, observing that the top positions run faster than the lower ones is, to a large extent, a mechanical consequence of the ranking's own construction and not an independent explanatory finding. The descriptive value lies in documenting the historical mark thresholds by position and their evolution over time, not in presenting the position-performance relationship as a causal relationship discovered by this study.

Effect of the Olympic cycle and strategic periodization

The season-by-season analysis (Table 4, Figure 4) shows good marks in some pre-Olympic years (2011: 9.89 s; 2015: 9.90 s), which was preliminarily interpreted as consistent with the long-cycle periodization models used in high-performance athletics. The fact that 2008 —an Olympic year— also shows a performance peak (9.93 s) could be related to the emergence of Bolt and his first world record (9.69 s in Beijing). However, the available data only allow us to state that Bolt contributed an exceptional record that lowered the mean of that season's top 20; they do not allow us to demonstrate that his emergence functioned as a "*collective catalyst*" that raised the performance of the rest of the sprinters. Testing that hypothesis would require comparing the mean, the median, and positions 2nd–20th with and without Bolt's record, and the differences before and after 2008, analyses that have not been conducted. It should also be clarified that the present study did not directly measure training-periodization variables; the Olympic-cycle effect is inferred solely from the aggregate seasonal pattern of marks and should therefore be understood as a tentative theoretical explanation and not as a causal finding of this work.

Talent, long-term development, and applications for coaches

It is precisely in the field of talent identification and development where the concept of an effective performance window (ages 25–32), rather than that of a single optimal age, acquires its greatest scientific and applied value. The findings of this study naturally integrate with evidence that early success does not predict senior elite performance, reinforcing the idea that talent-identification systems should prioritize an athlete's longitudinal progression over a broad age window, rather than isolated results in youth categories.

The results of the present study, by placing the optimal age at 29 years with a mean improvement of 0.04 s/year, have direct implications for talent identification and development systems. In contrast to the common bias of identifying talent based on performance in youth categories, recent literature is unequivocal: youth success is not a good predictor of elite adult sprint performance. Only 17% of sub-18 men in the world top

50 went on to reach the absolute top 50 according to Boccia et al. (2021), and Boccia et al. (2018) confirmed with Italian athletes that national elite sprinters reached their best mark later than lower-level athletes.

The model presented in this study offers coaches a quantitative reference framework for three key applications: (1) Evaluation of individual trajectory: comparing an athlete's progression with the described population curve allows identification of whether the sprinter is progressing in line with the elite trend, or whether they are in a plateau requiring methodological intervention; (2) Long-term planning: knowing that the effective window extends between ages 25 and 32 supports resistance to excessively early specialization and backs the investment of resources in athletes aged 20–24 who have not yet reached their performance ceiling; (3) Decline management: the post-peak deterioration rate of 0.0006 s/year is gradual enough that well-trained athletes aged 30–34 can maintain competitive levels within the world top 20, provided that training is specifically oriented toward preserving horizontal force production and stride technical efficiency (Morin et al., 2015; Samozino et al., 2022; Pantoja et al., 2016).

The analysis by Agudo-Ortega et al. (2024) with Spanish sprinters adds an additional element: performance in the sub-23 category ($\beta = 0.51$, $p < .001$) was the strongest predictor of participation in the absolute elite, far above sub-18 or sub-16 performance. This finding reinforces the need to maintain longitudinal tracking of the athlete at least until age 23 before making judgments about their elite potential, and to design training programmes that maximise progression within this critical age window.

Strengths of the model and positioning within the literature

The main strength of this work compared with previous mathematical models (Heazlewood, 2006; Shaw, 2012; Nevill & Whyte, 2005) lies in the fact that the smooth model and the mixed polynomial model fit the actual observed data (428 records, 20 seasons), rather than fitting predetermined functions applied to a single record (the world record). This distinction is fundamental: ARIMA models based on the world record offer good historical precision but limited applicability to individual training (Bartosz-Jefferies et al., 2025), whereas analysis of the top 20 of the ranking reflects the performance of a collective representative of the global elite.

The inclusion of a random term in the mixed model allows control of inter-individual variability, a frequent limitation in classical regression models applied to longitudinal athlete data. As detailed in section 2.2, the random athlete effect explains a substantial proportion of the total variability (ICC = 0.32), confirming that ignoring the athlete grouping structure would have underestimated the model's standard errors. However, the lack of information on the number of unique athletes and their repetition rate in the sample prevents fully assessing the risk that a small number of long-career athletes may dominate the estimate. In addition, the 20-season period (1998–2017) provides sufficient temporal stability so that the results are not biased by isolated exceptional events, although Bolt's presence during the 2008–2017 period represents a confounding factor that warrants attention. In this regard, the fact that the model identifies an optimal age of 29 years — rather than 23 years, the age at which Bolt set his first records— suggests that the model adequately captures the collective trend of the elite beyond exceptional individual phenomena.

Limitations and future directions

Among the limitations of the study, the following stand out: (a) its descriptive and retrospective nature, which does not allow causal relationships to be established; (b) the absence of individual data on training load, injuries, and longitudinal biomechanical variables; (c) the strong representation of North America (71.5%), which may condition the results of the global model; (d) the exclusion of female athletes; and (e) the impossibility of determining, from the available documentation, the number of unique athletes making up the

428 records analysed and their repetition rate across the 20 seasons, as well as an unresolved discrepancy between the 428 observations of the descriptive sample and the 408 observations on which the mixed model was fitted (Table 5). This limitation prevents fully ruling out the disproportionate influence of a small number of long-career elite athletes on the estimate of the optimal age and is acknowledged as an unresolved limitation of the present study. Future research should: (i) replicate the analysis including female athletes and compare developmental profiles between sexes; (ii) cross-reference age and performance data with training-load records to test hypotheses about the causes of the plateau and the decline; (iii) extend the analysis period to 2024–2025 to examine the impact of new competition footwear technology, the evolution of track surfaces, and the recent emergence of sprinters such as Noah Lyles or Marcell Jacobs; (iv) apply machine-learning models —such as those used by Tam and Yao (2024) to predict the velocity-time curve in sprinting— to improve individual predictive accuracy; and (v) recalculate the number of unique athletes and their repetition rate, and conduct a sensitivity analysis excluding athletes with the highest number of appearances, should the original individualized database become available.

CONCLUSIONS

The interaction between competition age and performance in the 100-meter sprint does not follow a linear pattern but rather fits a second-degree polynomial model. The empirical evidence from 20 seasons of world elite competition, contextualized within the framework of recent scientific research, allows the following conclusions to be established:

It should be noted that the finding with the greatest robustness and practical applicability is the concept of the effective performance window (conclusion 1), while the reference to a single optimal age of 29 years (conclusion 2) should be interpreted as a secondary population-level association.

There is an effective window of maximum performance between ages 25 and 32, with a mean mark stabilized around 9.97 s and lower variability than at the age extremes. This window is consistent with international data from Haugen et al. (2018) and Kotuła et al. (2025), although slightly wider than that observed in national studies (Agudo-Ortega et al., 2024: peak age 25.31 years for Spanish sprinters), reflecting the greater maturation latency in the context of world elite competition.

Age 29 constitutes the population-level age associated with the best records in the world elite, with a mean population improvement of 0.04 s/year up to that point and a subsequent decline of 0.0006 s/year, theoretically attributable to progressive changes in fibre composition, explosive force production, and mechanical efficiency (Korhonen et al., 2006; Pantoja et al., 2016). This trend reflects a group-level association and does not guarantee an individual trajectory of continuous improvement up to that age.

The plateau observable between ages 22 and 25 (9.97 s, 43% of the sample) could be compatible with an adaptive plateau related to the need for optimization of the individual force-velocity profile, although the present study did not measure this variable and cannot directly assess this mechanism. Only 17% of young sub-18 top-50 sprinters reach the absolute top 50 (Boccia et al., 2021), reinforcing the need to evaluate talent based on longitudinal progression rather than a single-point result.

The world ranking demands marks from 9.76 s (1st place) to 10.00 s (positions 12th–20th). Performance differences on the podium are statistically significant in the seasons of greatest competitive heterogeneity (Kotuła et al., 2025).

North America dominates the event with 71.5% of records and a mean mark of 9.95 s.

The smooth models and the mixed polynomial model are the most suitable for representing the reality of the 100-meter event, overcoming the limitations of the predetermined mathematical functions used in the classic literature and offering a valid long-term planning tool for high-performance coaches.

AUTHOR CONTRIBUTIONS

All authors meet the criteria for authorship in accordance with established ethical guidelines. Contributions are specified according to the CRediT (Contributor Roles Taxonomy) as follows: Conceptualisation: Maria Carmen Rodriguez-Fernandez. Methodology: Maria Carmen Rodriguez-Fernandez, Jose Fernando Arroyo-Valencia. Formal analysis: Maria Carmen Rodriguez-Fernandez. Investigation: Maria Carmen Rodriguez-Fernandez, Jose Fernando Arroyo-Valencia. Data curation: Maria Carmen Rodriguez-Fernandez. Writing – original draft: Maria Carmen Rodriguez-Fernandez. Writing – review & editing: Maria Carmen Rodriguez-Fernandez. Supervision: Maria Carmen Rodriguez-Fernandez.

All authors have critically reviewed and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

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CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript.

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In accordance with current publishing ethics and transparency recommendations, artificial intelligence (AI) tools were used solely to assist with translation and language editing, with the aim of improving clarity and readability. No AI tools were used in the generation of scientific content, including the study design, data collection, analysis, interpretation of results, or the formulation of conclusions. The authors retain full responsibility for the content of the manuscript and confirm its originality, integrity, and accuracy.

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