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ORIGINAL ARTICLE

Distance-dependent performance scaling across competitive representation pools in elite road runners

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ABSTRACT

Endurance running performance is usually compared at single events, and less is known about how the performance ceiling of a competitive pool changes across race distances. This study compared the distance scaling of all-time top-10 road-running performances across three competitive representation pools: Malaysia, Southeast Asia, and the broader Asian pool. The top ten all-time 10 km, half-marathon, and marathon performances for men and women in each pool were retrieved from the World Athletics database, giving 180 performance records contributed by 99 athletes. Running speed was analysed with linear mixed-effects models that included race distance, representation pool, gender, and age as fixed effects and athlete as a random intercept. The primary estimand was proportional change in speed across distance, estimated on log-transformed speed and summarised as a log-log scaling exponent. On the log scale, the Distance × Region (representation pool) interaction was significant ($F(4, 139.7) = 6.71$, $p < .001$, approximate partial $\eta^2 = .16$, 95% CI [.05, .26]), whereas no statistically significant Distance × Gender or three-way interaction was detected. The Southeast Asian men's list showed the steepest scaling exponent ($b = -0.084$, 95% CI [−0.100, −0.068]) and a 12.45% decline in mean speed from 10 km to marathon, and its exponent was steeper than that of the Asian men's list (difference −0.039, 95% CI [−0.067, −0.011]). No statistically significant difference in scaling was detected between the Malaysian and Asian pools, although the Malaysian lists had the lowest absolute speeds. The log-scale Distance × Region interaction was retained in sensitivity analyses allowing unequal residual variances, using each athlete's fastest record per distance, and restricted to post-2017 performances. Age was not associated with additional variation in speed within this selected sample. These findings support examining performance scaling across distances when benchmarking competitive representation pool.

Keywords: performance analysis; marathon; physical endurance; gender differences; athlete naturalisation; power law; linear mixed-effects model; Southeast Asia.

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INTRODUCTION

Across road-running events, mean sustainable speed declines as race distance increases. For record performances, race time is well approximated by a power law of distance with an exponent slightly above one (Riegel, 1981). If race time is proportional to distance raised to the power *a*, mean speed is proportional to distance raised to the power 1 − *a*, so the corresponding speed exponent is negative. Analyses of large performance databases show that this exponent varies between runners and carries information beyond absolute speed (Blythe & Király, 2016; Emig & Peltonen, 2020). How performance scales with distance is therefore a characteristic in its own right, distinct from the level of performance at any single distance.

Prior research has identified several moderators of distance-related performance. At the level of the individual athlete, the capacity to resist physiological deterioration during prolonged exercise has been termed durability and proposed as a fourth determinant of endurance performance (Jones, 2024; Maunder et al., 2021). Durability is measured by repeated physiological assessment within athletes and appears to be trainable (Zanini, Folland, & Blagrove, 2025; Zanini, Folland, Wu, et al., 2025). Archival performance lists cannot measure it, so any list-derived index of scaling is a cohort-level descriptor rather than a durability measure. Gender differences are also well documented, with men's elite performances on average approximately 10 to 12% faster than women's (Hunter et al., 2023; Hunter & Senefeld, 2024). These differences rest on gender-specific physiology across several systems that shape the integrative response to exercise (Ansdell et al., 2020). Some of these characteristics may favour women as event duration increases (Besson et al., 2022; Tiller et al., 2021). The gap also widens where fewer women compete, which points to the depth of the women's competitive field (Senefeld et al., 2016). Because women's performances are slower in absolute terms, an identical proportional decline produces a smaller absolute decline in metres per second. Changes in the gender gap with distance must therefore be judged on a proportional scale. Age is a further moderator, with endurance performance typically peaking between the late twenties and mid-thirties (Allen & Hopkins, 2015; Tanaka & Seals, 2008). In all-time lists, however, the observable age range is narrow, and the age-performance relationship may be attenuated because athletes who sustain high training loads preserve their physiological capacity for longer (Valenzuela et al., 2020).

The composition of high-level road-running performance lists varies across national and regional representation pools. East African athletes have long dominated road running. This pattern has been attributed to training environment, altitude exposure, sociocultural factors, and competitive infrastructure rather than to a single genetic factor (Grivas et al., 2024; Marc et al., 2017; Scott et al., 2003). Archival analyses of top-ranked performances from 10 km to ultra-distances show persistent Kenyan and Ethiopian dominance alongside smaller national clusters at longer distances (Nikolaidis et al., 2017). National representation and athlete development are also not synonymous, because several federations, including Gulf-state federations in distance running, have naturalised athletes born and developed elsewhere (Reiche & Tinaz, 2019). The present study therefore defines a competitive representation pool as the set of performances produced under the flags of a group of federations, irrespective of where the athletes were developed. Comparative evidence on distance scaling within Southeast Asian and Malaysian representation pools, which compete within the same regional championship system as the broader Asian pool, is limited.

Three gaps follow from this evidence. First, comparative studies of Asian road-running performance have mostly described absolute performance at single distances, and differences in absolute speed between performance lists are largely expected from how those lists are constructed. Second, whether the distance scaling of performance ceilings differs between representation pools, and whether it follows absolute performance level, has received limited attention. Third, studies using archival performance records seldom

account for athletes who contribute several records. The second gap persists partly because laboratory studies cannot sample the upper tail of several national pools at once, whereas official all-time lists can.

The aim of the present study was therefore to compare the distance scaling of all-time top-10 performance ceilings across the Malaysian, Southeast Asian, and broader Asian representation pools for 10 km, half-marathon, and marathon. Specifically, the study examined whether proportional speed decline across distance differed by representation pool and gender, and whether pools with higher absolute performance ceilings also showed smaller proportional declines. On the basis of the speed-distance power law, speed was hypothesised to decline with distance in every pool. Because no prior study had compared scaling across these pools, the between-pool comparison was treated as exploratory and no directional hypothesis was specified. The study offers a reproducible way of benchmarking representation pools by how their performance ceilings scale with distance.

METHODS

Study design

This was a cross-sectional observational study of archival performance records. Records were sampled in a balanced record-level arrangement across Race Distance (10 km, half-marathon, marathon), Region (representation pool: Malaysia, Southeast Asia, broader Asia), and Gender (men, women), with 10 records per cell. This balance applies to records, not athletes, because each cell contained 10 records but only 4 to 10 unique athletes. The analysis therefore conditions on selection into all-time top-10 lists, and records were treated as observations nested within athletes. Gender refers to the men's and women's competition categories under which World Athletics lists performances. Reporting was guided by the STROBE statement for observational studies (von Elm et al., 2007).

Ethical considerations

The study was a secondary analysis of publicly available competition records and athlete profile information, and no procedures were conducted with human or animal participants. Ethical approval for the use of publicly accessible archival data was obtained from the Sultan Idris Research Ethics Committee (Reference: 2025-0920-01). Informed consent was not sought because no contact with athletes took place and all records were already in the public domain. The study was conducted in accordance with institutional guidelines and the principles of the Declaration of Helsinki as they apply to research using publicly available data.

Data sources and athlete selection

Performance records were extracted from the publicly accessible World Athletics database (www.worldathletics.org), which lists official competition results for road-running events. Data were accessed between November and December 2025. For each distance, 10 km, half-marathon (21.0975 km), and marathon (42.195 km), the top ten all-time performances were retrieved separately for men and women in each of three representation pools. The pools were mutually exclusive and were assigned from the federation listed for each performance. The Malaysian pool comprised performances under the Malaysian flag. The Southeast Asian pool comprised performances under other Southeast Asian flags (in the final dataset, Indonesia, Thailand, Singapore, the Philippines, Myanmar, Vietnam, and Laos). The broader Asian pool comprised performances under other Asian flags (in the final dataset, Bahrain, Japan, Qatar, Kazakhstan, China, and the United Arab Emirates). No athlete contributed records to more than one pool or under more than one federation. Race times for Malaysian athletes were cross-checked against records held by the Malaysian Athletics Federation. Dates of birth were taken from World Athletics athlete profiles and, where unavailable, from other public records, to compute age at each performance. Records were eligible if they

were listed as official results for the respective road event in the source database. Course-level metadata, such as elevation profile and start-finish separation, were not available for all records and were not used as eligibility criteria. Course heterogeneity is therefore treated as residual variation rather than assumed to be absent. The sampling frame was therefore a census of the top ten all-time records in each cell rather than a random or convenience sample. Sample size was fixed by this design, so no a priori power calculation was performed.

Sample

The final dataset comprised 180 performance records contributed by 99 unique athletes, with 10 records in each of the 18 Region × Gender × Distance cells. After harmonising variant spellings of athlete names, 61 athletes contributed a single record and 38 contributed two or more (maximum nine). Each cell contained 4 to 10 unique athletes (Table 1). Overlap across distances was sparse: 19 athletes contributed records at both 10 km and half-marathon, 13 at both half-marathon and marathon, 9 at both 10 km and marathon, and 7 at all three distances. The composition of the broader Asian pool varied sharply with distance. Athletes representing Gulf-state federations produced 34 of its 60 records (15 athletes), comprising 15 of 20 records at 10 km, 15 of 20 at the half-marathon, and 4 of 20 at the marathon, where Japanese and Chinese athletes predominated. Age at the time of performance was M = 28.42 years (SD = 4.39, range 18 to 40). Under a published participant classification framework, the athletes ranged from Tier 3 (highly trained, national level) to Tier 5 (world class). The Malaysian lists were mainly at Tiers 3 and 4, and the broader Asian lists at Tiers 4 and 5 (McKay et al., 2022).

Performance measure

The race completion time (seconds) was retrieved from official records. Running speed (m/s) was computed by dividing race distance (in metres) by completion time (in seconds), which gives a common outcome unit across distances (Girardi et al., 2022). A common unit does not make race conditions comparable. Race distances were treated as their official lengths: 10,000 m for 10 km, 21,097.5 m for half-marathon, and 42,195 m for marathon.

Statistical analysis

Descriptive statistics were computed for each Region × Gender × Distance cell. Because records were nested within athletes, inference used linear mixed-effects models with a random intercept for athlete. The primary model for the central question used natural-log-transformed speed as the outcome. Race Distance, Region, Gender, and all their interactions were fixed effects, and age at performance (grand-mean centred) was a covariate. On the log scale, model contrasts are multiplicative differences in speed, and exponentiating a contrast gives a percentage difference. The Distance × Region interaction therefore tests whether proportional change across distance differs between pools. The same model fitted to untransformed speed is reported as a complementary analysis. Models were fitted by restricted maximum likelihood with sum-to-zero contrasts using the lme4 package in R version 4.3.3 (Bates et al., 2015; R Core Team, 2024). Type III F tests used Satterthwaite denominator degrees of freedom, with the Kenward-Roger approximation examined as a check (Kuznetsova et al., 2017; Luke, 2017).

A second model summarised scaling in one parameter per group: ln(speed) = β_0 + b ln(distance) + Region + Gender + Region × Gender + ln(distance) × (Region + Gender + Region × Gender) + β_1 age + u_j + ε. In this model, u_j is the random intercept for athlete j. Group-specific exponents (b) were estimated as the slope of ln(speed) on ln(distance) within each Region × Gender group, and a more negative b indicates a steeper decline. Pairwise differences in b between pools within each gender were estimated with Bonferroni-adjusted 95% confidence intervals (Lenth, 2024). This is a population-average scaling model for the record pools. It

does not estimate athlete-specific scaling, because only nine athletes contributed records at both 10 km and the marathon, too few to support random slopes. Follow-up analyses focused on interaction-specific contrasts, namely proportional decline from 10 km to marathon within each Region × Gender group, and main-effect comparisons are reported for context only.

The athlete variance component is summarised by the intraclass correlation (ICC). Its likelihood-ratio test was referred to a 50:50 mixture of χ^2_0 and χ^2_1 distributions, because the null value of a variance lies on the boundary of the parameter space (Self & Liang, 1987). Marginal and conditional R^2 were computed descriptively (Nakagawa & Schielzeth, 2013). Approximate partial η^2 values with 95% confidence intervals were derived from each *F* statistic and its degrees of freedom by noncentral *F* inversion (Steiger, 2004). They are reported for comparability with factorial designs and are not interpreted against conventional thresholds, because model contrasts with 95% confidence intervals carry the substantive interpretation. All tests were two-tailed, significance was set at $p < .05$, and non-significant results are described as absence of detected evidence rather than as equivalence.

Model assumptions were assessed from the residuals and athlete random intercepts of the primary model, using normal quantile-quantile plots, a Shapiro-Wilk test of the residuals, and residuals plotted against fitted values. Fixed effects in mixed models are generally robust to distributional departures, although individual datasets can give imprecise estimates (Schielzeth et al., 2020). Robustness was therefore examined directly with a model allowing a separate residual variance for each cell, a refit excluding the most influential athlete, and the cluster bootstrap described below. The heteroscedastic model used the varIdent variance structure of the nlme package (Pinheiro et al., 2023). Age × Distance, Age × Region, and Age × Gender interactions were tested to assess whether the age association varied across distance, pool, or gender.

Two descriptive indices complemented the models. The observed proportional decline in mean speed from 10 km to marathon was computed for each Region × Gender group as ((speed at 10 km − speed at marathon) / speed at 10 km) × 100. Segment declines were computed in the same way. Ninety-five per cent confidence intervals came from a cluster bootstrap with 5,000 resamples, in which athletes were resampled with replacement within each group (Field & Welsh, 2007). All observed records of a resampled athlete entered the cell means for the distances at which that athlete had records. The bootstrap therefore quantifies uncertainty arising from the observed list composition, not from individual athlete trajectories. Between-group differences in decline were judged from the bootstrap distribution of the difference. The gender gap was computed at each distance as the percentage by which mean speed in the women's list was lower than in the men's list. Model-based gaps with 95% confidence intervals were estimated from within-pool mixed models on log speed.

Four sensitivity analyses targeted the primary log-scale results. The first allowed a separate residual variance for each cell. The second retained only each athlete's fastest record per distance ($n = 137$), which prevents several records by one athlete at the same distance from dominating a cell, although it does not create matched athletes across distances. The third was restricted to performances from 2017 onward ($n = 131$; 78 athletes), selected to approximate the widespread use of advanced road-racing footwear (Bermon et al., 2021). The fourth excluded the most influential athlete identified in the diagnostics. An ordinary least squares ANCOVA treating all records as independent was also fitted to show the consequence of ignoring clustering. The cluster bootstrap was run in Python version 3.12 with NumPy version 2.4.

RESULTS

Sample characteristics

Table 1. Race time, age, and running speed of the top-10 records by representation pool, gender, and race distance.

Region	Gender	Distance	Records (*n*)	Athletes (*n*)	Race time (s) *M* ± *SD*	Age (yr) *M* ± *SD*	Speed (m/s) *M* ± *SD*
Malaysia	Men	10 km	10	8	1931.50 ± 61.45	25.10 ± 4.09	5.18 ± 0.17
		21 km	10	6	4120.50 ± 80.49	29.70 ± 2.26	5.12 ± 0.10
		42 km	10	7	8826.80 ± 159.23	31.70 ± 3.50	4.78 ± 0.09
	Women	10 km	10	10	2459.00 ± 121.89	30.70 ± 6.95	4.08 ± 0.21
		21 km	10	6	5216.40 ± 93.72	29.70 ± 4.99	4.05 ± 0.07
		42 km	10	9	11119.50 ± 433.63	32.30 ± 5.50	3.80 ± 0.15
SEA	Men	10 km	10	8	1779.10 ± 21.86	25.90 ± 3.70	5.62 ± 0.07
		21 km	10	9	3965.20 ± 94.03	28.70 ± 3.33	5.32 ± 0.13
		42 km	10	5	8574.10 ± 84.20	30.80 ± 3.68	4.92 ± 0.05
	Women	10 km	10	6	2077.40 ± 37.61	25.60 ± 4.12	4.82 ± 0.09
		21 km	10	8	4732.00 ± 134.53	26.60 ± 5.36	4.46 ± 0.13
		42 km	10	4	9710.70 ± 459.66	29.70 ± 4.76	4.35 ± 0.21
Asia	Men	10 km	10	8	1660.70 ± 25.12	27.90 ± 3.07	6.02 ± 0.09
		21 km	10	7	3566.60 ± 27.27	26.10 ± 3.54	5.92 ± 0.05
		42 km	10	8	7521.00 ± 22.55	27.90 ± 2.69	5.61 ± 0.02
	Women	10 km	10	7	1859.40 ± 41.72	27.70 ± 1.57	5.38 ± 0.12
		21 km	10	7	3989.30 ± 43.47	27.70 ± 3.20	5.29 ± 0.06
		42 km	10	10	8383.00 ± 26.67	27.70 ± 3.23	5.03 ± 0.02

Note. Records, number of performance records per cell; Athletes, number of unique athletes contributing to the cell; *M*, mean; *SD*, standard deviation; SEA, Southeast Asia.

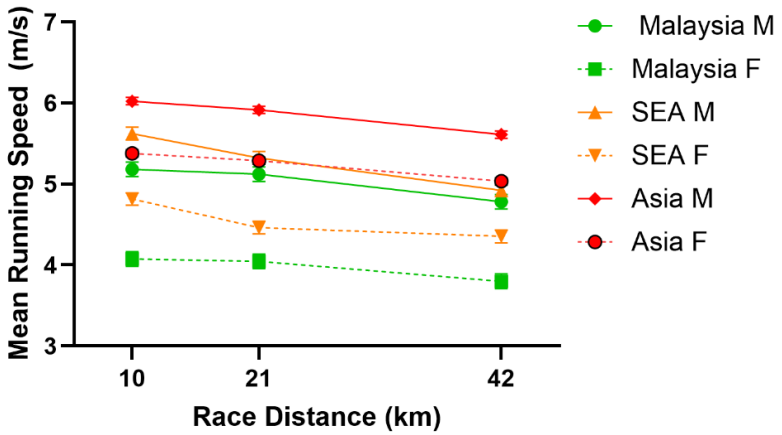

Figure 1. Mean running speed declined with distance in every top-10 list, and the Southeast Asian men's list converged towards the Malaysian men's list at the marathon. Points are cell means of running speed (m/s) and error bars are 95% confidence intervals, with 10 records per cell. Solid lines, men; dashed lines, women; M, men; F, women; SEA, Southeast Asia.

Table 1 and Figure 1 present the descriptive characteristics of the records by region, gender, and distance. In every group, mean race time increased and mean speed decreased with distance, and the men's lists were faster than the women's lists. The Asian-pool top-10 lists had the highest mean speeds, followed by the Southeast Asian and Malaysian lists, which reflects selection into the all-time lists rather than a finding in its own right. Cell mean ages ranged from 25.1 to 32.3 years.

Linear mixed-effects models

Table 2. Linear mixed-effects models of log-transformed and untransformed running speed by race distance, representation pool, and gender.

Source	df_1	df_2	*F*	*p*	Partial η² [95% CI]
A. ln(speed), primary model					
Age (covariate)	1	155.5	0.65	.422	.004 [.000, .047]
Race Distance	2	141.5	196.72	< .001	.735 [.665, .786]
Region	2	87.1	675.76	< .001	.939 [.917, .954]
Gender	1	86.7	1201.62	< .001	.933 [.907, .949]
Distance × Region	4	139.7	6.71	< .001	.161 [.050, .258]
Distance × Gender	2	143.0	2.06	.131	.028 [.000, .094]
Region × Gender	2	86.5	59.75	< .001	.580 [.444, .676]
Distance × Region × Gender	4	139.9	1.29	.277	.036 [.000, .090]
B. Speed (m/s)					
Age (covariate)	1	157.0	0.64	.425	.004 [.000, .048]
Race Distance	2	143.5	225.09	< .001	.758 [.694, .805]
Region	2	87.1	766.99	< .001	.946 [.926, .959]
Gender	1	86.6	1341.69	< .001	.939 [.917, .954]
Distance × Region	4	141.8	6.84	< .001	.162 [.051, .258]
Distance × Gender	2	144.9	6.85	.001	.086 [.015, .177]
Region × Gender	2	86.3	35.97	< .001	.454 [.298, .572]
Distance × Region × Gender	4	142.0	1.23	.302	.033 [.000, .086]

Note. Type III *F* tests with Satterthwaite denominator degrees of freedom; all models include age at performance (centred) as a covariate and athlete as a random intercept. Partial η² values are approximations derived from *F* and its degrees of freedom. Their 95% confidence intervals come from noncentral *F* inversion, and they are not interpreted against conventional thresholds. df_1, numerator degrees of freedom; df_2, denominator degrees of freedom; CI, confidence interval.

Records were strongly clustered within athletes (ICC = .60 in the log-speed model and .58 in the raw-speed model), and the athlete variance component was supported by the boundary-corrected likelihood-ratio test ($p < .001$). Marginal and conditional R^2 for the raw-speed model were .97 and .99. These values reflect the stratified construction of the lists and do not indicate out-of-sample predictive performance. In the primary log-speed model (Table 2, Panel A), the Distance × Region interaction was significant, $F(4, 139.7) = 6.71$, $p < .001$, approximate partial $\eta^2 = .16$ (95% CI [.05, .26]), providing evidence that proportional speed decline across distance differed between representation pools. No statistically significant Distance × Gender interaction, $F(2, 143.0) = 2.06$, $p = .131$, or three-way interaction, $F(4, 139.9) = 1.29$, $p = .277$, was detected. The Region × Gender interaction was significant, $F(2, 86.5) = 59.75$, $p < .001$, indicating that the gender gap differed between pools. The large main effects of distance, region, and gender are expected from list construction and are reported in Table 2 for context.

The raw-speed model (Table 2, Panel B) gave the same pattern for the Distance × Region interaction, $F(4, 141.8) = 6.84$, $p < .001$, but also showed a significant Distance × Gender interaction, $F(2, 144.9) = 6.85$, $p = .001$. Because this interaction was not reproduced on the log scale, evidence for a gender-by-distance difference was sensitive to the outcome scale, which is consistent with the lower absolute speeds of the women's lists. The Kenward-Roger approximation produced the same inferences in both models. An ordinary least squares ANCOVA that treated all records as independent (error df = 161) inflated the *F* statistics for the between-athlete effects of region and gender but led to the same inferences. Within this selected performance archive, age was not associated with additional variation in speed (log model: $F(1, 155.5) = 0.65$, $p = .422$), and no age-by-factor interaction was detected (all $p \geq .717$).

Residuals of the primary model departed from normality (Shapiro-Wilk $W = .96$, $p < .001$), with a moderate right tail in both the residuals and the athlete random intercepts. The largest random intercept belonged to one athlete in the Malaysian women's lists, and residual spread was larger in the slower cells.

Proportional speed decline and scaling exponents

Table 3. Model-based proportional decline in speed from 10 km to marathon and log-log scaling exponents by representation pool and gender.

Region	Gender	Athletes (n)	Model-based decline, 10 to 42 km (%) [95% CI]	Exponent b [95% CI]
Malaysia	Men	16	8.45 [6.38, 10.49]	−0.058 [−0.075, −0.041]
	Women	17	7.57 [5.94, 9.18]	−0.053 [−0.067, −0.040]
SEA	Men[a]	15	11.28 [9.40, 13.12]	−0.084 [−0.100, −0.068]
	Women	14	9.12 [7.38, 10.83]	−0.067 [−0.081, −0.053]
Asia	Men	18	6.67 [4.57, 8.73]	−0.045 [−0.061, −0.028]
	Women	19	6.08 [4.00, 8.11]	−0.042 [−0.058, −0.026]

Note. Values are group-level, list-derived descriptors from the log-speed mixed model, adjusted for age and athlete, with 95% confidence intervals. Athletes, unique athletes contributing to the group across distances; *b*, scaling exponent, where a more negative value indicates a steeper decline; CI, confidence interval; SEA, Southeast Asia. [a] The Southeast Asian men's marathon list contained five athletes, three of whom contributed eight of its ten records.

Figure 2 and Table 3 summarise the distance scaling of each top-10 list. The Southeast Asian men's list showed the largest observed decline from 10 km to marathon (12.45%, 95% CI [11.41, 13.52]), with declines of 5.30% from 10 km to half-marathon and 7.55% from half-marathon to marathon. It also showed the steepest scaling exponent ($b = −0.084$, 95% CI [−0.100, −0.068]), equivalent to about 5.6% lower speed for each doubling of distance. In the bootstrap, its observed decline exceeded that of every other list except the Southeast Asian women's list (for example, reported difference from the Malaysian men's list = 4.57 percentage points, 95% CI [2.07, 6.80]). The Log Distance × Region interaction in the exponent model was significant, $F(2, 161.0) = 8.57$, $p < .001$, whereas no statistically significant Log Distance × Gender, $F(1, 162.0) = 1.68$, $p = .197$, or three-way interaction, $F(2, 161.7) = 0.51$, $p = .603$, was detected. Among men, the Southeast Asian exponent was steeper than the Asian exponent (difference = −0.039, 95% CI [−0.067, −0.011]; Table 4), whereas the confidence interval for its difference from the Malaysian exponent included zero (−0.026, 95% CI [−0.054, 0.002]). No statistically significant difference in exponents between pools was detected among women. The Malaysian lists had the lowest absolute speeds at every distance. Even so, no statistically significant difference in scaling from the Asian lists was detected for either gender (men: −0.013, 95% CI [−0.042, 0.015]; women: −0.011, 95% CI [−0.037, 0.015]). The model-based decline, which adjusts for age and athlete, was smaller than the observed decline for the Southeast Asian men's list (11.28% vs 12.45%) and larger for the Malaysian men's list (8.45% vs 7.73%). The difference between these two lists therefore narrowed after partial adjustment for athlete composition.

Table 4. Pairwise differences in log-log scaling exponents between representation pools within each gender.

Gender	Comparison	Difference in *b*	95% CI	*p*
Men	SEA − Asia	−0.039	[−0.067, −0.011]	.002
	SEA − Malaysia	−0.026	[−0.054, 0.002]	.076
	Malaysia − Asia	−0.013	[−0.042, 0.015]	.794
Women	SEA − Asia	−0.025	[−0.052, 0.002]	.074
	SEA − Malaysia	−0.014	[−0.038, 0.010]	.500
	Malaysia − Asia	−0.011	[−0.037, 0.015]	.883

Note. Differences are the first-named minus the second-named pool, so negative values indicate a steeper decline in the first-named pool. Estimates are differences in estimated marginal trends from the exponent mixed model; confidence intervals and *p* values are Bonferroni-adjusted for three comparisons per gender. *b*, scaling exponent; CI, confidence interval; SEA, Southeast Asia.

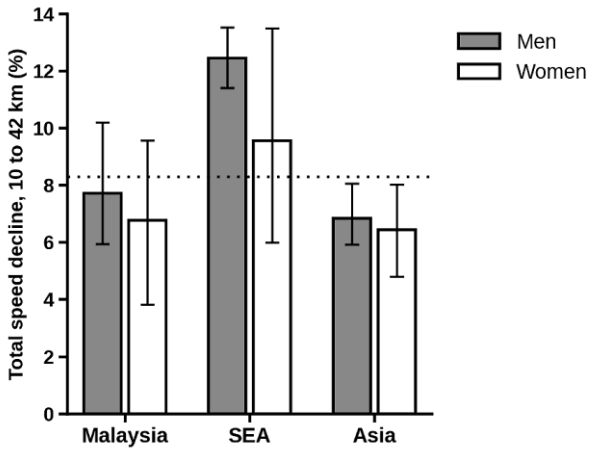

Figure 2. The Southeast Asian men's list showed the largest observed decline in mean speed from 10 km to marathon. Bars are list-derived declines computed as $((\text{Speed}_{10\text{km}} - \text{Speed}_{42\text{km}}) / \text{Speed}_{10\text{km}}) \times 100$ from cell-mean speeds, and error bars are athlete-level cluster-bootstrap 95% confidence intervals. The dotted line marks the mean across the six lists (8.30%); SEA, Southeast Asia.

Gender gap across distances within representation pools

Within-pool mixed models on log speed estimated the gender gap at each distance (Figure 3). In the Malaysian pool, the model-based gap was 21.5% (95% CI [19.0, 24.0]) at 10 km, 21.4% (95% CI [18.8, 23.9]) at the half-marathon, and 20.9% (95% CI [18.4, 23.4]) at the marathon, and no statistically significant change across distance was detected, $F(2, 41.4) = 0.10$, $p = .909$. In the Asian pool, the corresponding gaps were 10.9% (95% CI [9.8, 11.9]), 10.5% (95% CI [9.4, 11.5]), and 10.3% (95% CI [9.3, 11.3]), again with no detected change, $F(2, 52.3) = 0.38$, $p = .685$. In the Southeast Asian pool, the gap changed with distance, $F(2, 44.7) = 4.71$, $p = .014$. It was 15.4% (95% CI [13.3, 17.4]) at 10 km and 16.6% (95% CI [14.6, 18.5]) at the half-marathon, then narrowed to 13.3% (95% CI [11.0, 15.5]) at the marathon; the half-marathon to marathon change was significant ($p = .005$), whereas the 10 km to half-marathon change was not ($p = .284$).

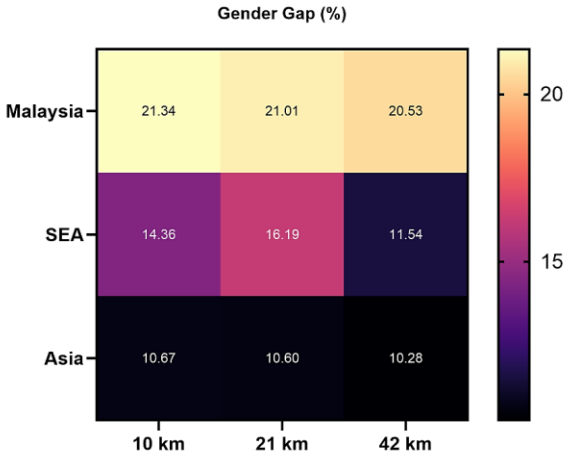

Figure 3. The gender gap was largest in the Malaysian pool and smallest in the broader Asian pool, and it changed with distance only in the Southeast Asian pool. Values are descriptive cell-mean percentages by which mean speed in the women's top-10 list was lower than in the men's list; model-based estimates with 95% confidence intervals are reported in the text. SEA, Southeast Asia.

The primary log-scale Distance × Region interaction was retained in every sensitivity analysis. It was significant with cell-specific residual variances (F = 13.63, p < .001); with each athlete's fastest record per distance, F(4, 70.2) = 5.09, p = .001; with performances from 2017 onward, F(4, 103.6) = 4.00, p = .005; and after excluding the most influential athlete, F(4, 149.0) = 9.37, p < .001. The Log Distance × Region interaction in the exponent model was retained with cell-specific variances (p < .001) and in the fastest-record dataset (p = .022), but it did not reach significance in the post-2017 subset, F(2, 113.7) = 2.54, p = .083. The difference between the Southeast Asian and Asian men's exponents was retained in both the fastest-record analysis (difference = −0.039, 95% CI [−0.073, −0.005]) and the post-2017 analysis (−0.033, 95% CI [−0.065, −0.001]). No statistically significant log-scale Distance × Gender interaction was detected in any sensitivity analysis. The Distance × Region association was therefore retained in the post-2017 sensitivity analysis, although evidence for differences in the summary exponent was weaker in that smaller and unbalanced subset (2 to 10 records per cell).

DISCUSSION

This study compared the distance scaling of all-time top-10 performance ceilings across Malaysian, Southeast Asian, and broader Asian representation pools. Three findings are central. First, the log-speed model provided evidence that proportional decline across distance differed between pools, and this result was retained in all sensitivity analyses. Second, scaling did not follow absolute level: the Malaysian lists were slowest, yet no difference in scaling from the Asian lists was detected, whereas the Southeast Asian men's list declined most. Third, no statistically significant gender-by-distance interaction was detected on the log-speed scale, and the gender gap changed with distance only in the Southeast Asian pool. All three findings describe selected performance ceilings, not the typical elite runner or individual athletes.

The decline in speed with distance is consistent with the speed-distance power law. A time exponent of about 1.06 for record performances implies a speed exponent of about −0.06, because the speed exponent equals one minus the time exponent (Riegel, 1981). The exponents estimated here, −0.042 to −0.084, bracket this value, which supports the face validity of the scaling model. The larger decline between half-marathon and marathon in most lists agrees with evidence that the power-law relationship underestimates marathon times relative to shorter races (Vickers & Vertosick, 2016). Possible contributors include race-specific pacing, training exposure, and field composition, but these mechanisms were not measured and cannot be tested here. The main contribution of the study is to show that scaling can be quantified for each representation pool from public records and that pools differ in it.

The partial dissociation between absolute level and scaling is best read at the level of the lists. The Southeast Asian men's ceiling was faster than the Malaysian ceiling at 10 km but converged towards it at the marathon. The Malaysian ceiling, although slowest, scaled in a way that could not be distinguished from the Asian ceiling. Because each decline compares separate top-10 lists, a steeper decline can arise whenever a pool's shorter-distance list contains different, or more specialised, athletes than its marathon list. Evidence from large individual-level databases indicates that the scaling exponent is related to event specialisation (Blythe & Király, 2016). This evidence is consistent with the compositional explanation. The Southeast Asian men's marathon list illustrates the point, because three athletes contributed eight of its ten records. After partial adjustment for athlete composition, the model-based decline for this list was smaller than the observed decline, and the confidence interval for its exponent difference from the Malaysian list included zero. The result is therefore a list-level scaling pattern and does not establish that Southeast Asian men lose more speed with distance than other athletes do. Field depth, specialisation, and pacing across distances are hypotheses for future work (Ristanović et al., 2023; Tangporm et al., 2025; Thuany et al., 2023).

The composition of the Asian pool is part of the definition of that group rather than a peripheral limitation. Athletes representing Gulf-state federations produced 15 of 20 Asian-pool records at both 10 km and the half-marathon but only 4 of 20 at the marathon, where Japanese and Chinese athletes predominated. The Asian decline and exponent therefore partly compare different athlete populations at shorter and longer distances. A sensitivity analysis excluding Gulf-state records could not be estimated, because every record in the Asian men's 10 km list came from a Gulf-state federation. Such an analysis would require separately extracted top-10 lists for non-Gulf Asian federations. Interpretations involving the Asian pool are therefore limited to the representation pool as defined. Treating national teams as competitive environments shaped by migration and nationality transfer is consistent with research on athlete migration (Horowitz & McDaniel, 2015; Jansen et al., 2018; Reiche & Tinaz, 2019). For federations, the representation pool is the relevant benchmark, because it is the field their athletes meet at championships. For questions about athlete development, the same lists can mislead, and coding developmental origin separately from representation would allow the two questions to be addressed separately.

The gender-gap results depended on the scale of measurement. A Distance × Gender interaction was present for untransformed speed but was not detected for log speed. The smaller absolute decline in the women's lists is therefore consistent with their lower absolute speeds rather than with a different proportional decline. Across the three distances studied, these selected performance ceilings did not support a monotonic widening of the gender gap with distance. The Asian-pool gap of about 10% is consistent with the 10 to 12% reported for elite cohorts (Hunter et al., 2023). The Malaysian gap was about twice as large (about 21%), with the Southeast Asian pool intermediate (about 13 to 17%). Differences in the depth of the women's competitive field, developmental support, and participation structures are possible explanations that were not measured (Hunter et al., 2023; Senefeld et al., 2016). The Gulf-state composition of the Asian women's 10 km and half-marathon lists may also affect the composition of the observed gap.

Within this selected performance archive, age was not associated with additional variation in speed. Age was measured at each performance, so it was partly confounded with athlete identity and performance era, and all-time lists span a restricted age window (cell means 25 to 32 years). This result should not be read as evidence that age is unimportant for endurance performance, which is well documented (Ganse & Degens, 2021; Tanaka & Seals, 2008).

Strengths and limitations

This study has several strengths. The records are official competition results from a public database. The mixed models account for athletes contributing several records to a balanced record-level sampling structure. Testing proportional scaling on the log scale separates differences in scaling from differences in absolute speed, and the decline index and exponent are reproducible from public results, with uncertainty quantified at the athlete level. The primary log-scale result was retained across sensitivity analyses addressing unequal variances, repeated records, the footwear era, and an influential athlete.

Several limitations require consideration. First, and most important, the data are an extreme-value sample. Top-10 all-time lists condition on selection into the upper tail of each pool, each cell contained only 4 to 10 unique athletes, and overlap of athletes across distances was sparse. This selection inflates absolute speeds relative to the typical elite runner, and scaling in larger representative samples may differ in either direction. Second, the decline index and scaling exponent compare separate lists at each distance and have not been validated against individual physiological durability. Where a pool's shorter-distance list contains more specialised athletes than its marathon list, the index will overstate the decline that individual athletes experience. Third, the Asian pool includes Gulf-state athletes developed outside Asia, its composition

changed markedly with distance, and a Gulf-excluded analysis was not estimable. Because Gulf-state athletes dominated the shorter distances, this composition probably raised the Asian 10 km and half-marathon ceilings and thereby inflated the Asian decline. Fourth, era composition differed between cells, and recent-heavy lists will have benefited more from advanced footwear and pacing technology, which inflates speeds in those cells and could bias between-pool comparisons in either direction. Fifth, course-level metadata were unavailable, so course heterogeneity adds unmodelled variation that reduces precision and may obscure smaller interactions. Sixth, residuals and random effects showed a moderate right tail, so the nominal coverage of the confidence intervals may not hold exactly. Finally, age was confounded with athlete identity and era, which attenuates the estimated age association, and no physiological, training, or environmental data were available, so the design does not support mechanistic claims.

Practical applications and future directions

Performance analysts and national coaches responsible for benchmarking in national athletics federations should compare representation pools on scaling exponents as well as on absolute times. Absolute level and distance scaling were partially dissociable within these selected ceilings. A single-distance performance should not be assumed to characterise how a pool's performance ceiling scales to longer distances. The decline index and exponent can be computed at no cost from public results, but they reflect list composition as well as athlete capacity and are not validated for coaching diagnosis or individual decisions. The larger gender gap in the Malaysian pool than in the Asian pool may identify a performance-development disparity worthy of further investigation.

The next study needed is a longitudinal analysis of Southeast Asian and Malaysian runners with official results at two or more of the three distances. Such an analysis would test whether the list-level differences in scaling observed here also appear within athletes. Separately extracted top-10 lists for non-Gulf Asian federations, coded for developmental origin, would test whether the Asian scaling pattern depends on the Gulf-state composition of its shorter-distance lists. Applying the same approach to African, European, North American, and South American pools would show whether the dissociation between absolute level and scaling is specific to the Asian context.

CONCLUSION

In all-time top-10 road-running performance ceilings, proportional speed decline from 10 km to marathon differed between the Malaysian, Southeast Asian, and broader Asian representation pools. The Southeast Asian men's list declined most (12.45%), with a scaling exponent steeper than that of the Asian men's list. No statistically significant difference in scaling was detected between the Malaysian and Asian lists, despite the lower absolute speeds of the Malaysian lists. Absolute performance level and distance scaling are therefore partially separable properties of a pool's performance ceiling. Federation performance analysts should benchmark pools on both properties. Within-athlete, multi-distance records are now needed to test whether these list-level patterns hold for individual runners.

AUTHOR CONTRIBUTIONS

All authors meet the established criteria for authorship. Contributions are reported according to the CRediT taxonomy as follows:

Conceptualisation: Haashwein Moganan, Hussain Haleem. Methodology: Haashwein Moganan, Rumi Iqbal Doewes. Formal analysis: Haashwein Moganan. Investigation: Haashwein Moganan, Chin Hong Zhang, Chin

Xin Zhang. Data curation: Haashwein Moganan, Chin Hong Zhang, Chin Xin Zhang. Writing – original draft: Haashwein Moganan. Writing – review & editing: Haashwein Moganan, Rumi Iqbal Doewes, Hussain Haleem, Chin Hong Zhang, Chin Xin Zhang. Supervision: Rumi Iqbal Doewes.

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.

AI USE DISCLOSURE

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.

DATA AVAILABILITY

The performance records analysed are publicly available from the World Athletics database. The compiled dataset is available from the corresponding author on reasonable request; it is not deposited publicly because it is compiled from a third-party database. The R and Python analysis code is available from the corresponding author on reasonable request.

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