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# Field-based modelling of segment speed in trail running using GPS and course characteristics

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**ABSTRACT**
Trail running performance is characterised by large fluctuations in speed due to changes in slope, terrain, and race progression, which are not well captured by models derived from road running. This study aimed to develop a field-based model of segment speed in trail running using GPS data and course characteristics. Data were collected from 517 runners competing in 20 short-distance trail races (10–35.6 km) in Belgium, primarily involving recreational participants and low-to-moderate technical terrain. Race courses were segmented using the Trail Segment Analysis Tool (TSAT), with segment boundaries and technical difficulty determined through on-site reconnaissance. GPS data were used to quantify segment length, mean slope, and participant speed. Exploratory analyses revealed a strong non-linear relationship between segment speed and slope, with weaker associations for technical difficulty and race position. A multiple regression model incorporating these variables and average trail speed explained 81% of the variance in segment speed. Maximal speeds occurred on moderate downhills (~–8%), with marked reductions on steeper gradients. Within this specific race context, these findings show that accessible field-derived data can support robust segment-level performance modelling and provide practical insights for pacing analysis and race planning in trail running.

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**KEYWORDS**
Trail running; pacing; performance analysis; measurement; field data

## 1. Introduction

Trail running presents substantial variability in pacing due to alternating uphills, downhills, flat sections, and technical terrain (de Waal et al., 2025; Jaén-Carrillo et al., 2025; Warren et al., 1986). These rapid changes in slope and surface complexity impose continuous adjustments to stride mechanics and foot placement often accompanied by changes in running speed (Giandolini et al., 2015; Mohr et al., 2023). Existing prediction models developed for road running are therefore insufficient to describe performance in trail contexts (de Waal et al., 2021; Ehrström et al., 2018). On steep inclines, walking can become more economical than running (Ardigò et al., 2003; Giovanelli et al., 2016), whereas technical surfaces such as roots, rocks or mud require controlled foot placement and gait adaptations that reduce speed (Mohr et al., 2023; Warren et al., 1986). As

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a result, pacing during trail running reflects a complex interaction between terrain constraints and performance capacity.

The energetic influence of slope has been well characterised in laboratory settings (Dewolf & Willems, 2019; Minetti et al., 2002), yet these controlled models do not account for the stochastic and multidimensional nature of real trail environments. Consequently, there is still limited understanding of how course characteristics interact to influence speed in competitive trail running. The increasing availability of GPS recordings, combined with course-segmentation applications, now provides opportunities to quantify terrain features in situ and to develop field-based models of performance. In addition to GPS-based approaches, recent developments in wearable technologies have enabled the estimation of mechanical power, energy expenditure, and metabolic load in running. For example, mechanical running power metrics derived from wearable sensors have been shown to characterise differences in energy expenditure across slope conditions (Gravina-Cognetti et al., 2025), and systematic reviews highlight how wearable sensors (e.g. inertial measurement units, foot-mounted power metres) are increasingly used to assess gait, load, and performance in real-world running contexts (Mason et al., 2023). These technologies provide valuable internal and external load insights but require dedicated sensors and may be limited by adoption and data accessibility in large or retrospective datasets. Consequently, there remains a need for complementary field-based methods that can leverage widely available GPS and course profile data to model performance across heterogeneous terrain. The recently introduced Trail Segment Analysis Tool (TSAT) allows segment-level extraction of course descriptors and facilitates systematic analysis of speed variations during trail races (De Cock et al., 2025).

The objective of this study was to develop a field-based model to predict segment speed in trail running using GPS-derived data and course characteristics, with the aim of providing a practical and accessible framework for performance analysis and pacing strategy in short-distance trail running contexts with heterogeneous segment characteristics.

## 2. Materials and methods

### 2.1. Participants and races

Data were collected from 517 recreational runners (75% men; age: 38 ± 11 years) participating in 20 short-distance trail races organised in Belgium (Table 1). Race distances ranged from 10 to 35.6 km, with a positive elevation gain between 245 and 1,431 m, corresponding to an average ascent of 30.9 ± 7.6 $\text{m}\cdot\text{km}^{-1}$. The proportion of off-road terrain across races was 79.3 ± 12.6%. GPS activity data originated from recordings generated by the participants' own GPS watch during competition. With participant consent, performance data were accessed via the STRAVA platform (Strava Inc.), which was used as a visualisation interface. Only data from participants enrolled in the study were collected, and no automated extraction or bulk data harvesting was performed. GPS-derived measures of distance have demonstrated acceptable accuracy in endurance running competitions, including ultramarathon events (Johansson et al., 2020). Furthermore, the validity and reliability of STRAVA-derived segment metrics in running

**Table 1.** Descriptive characteristics of the 20 trail races included in the study.

A. Race Characteristics

| Variable | Mean ± SD | Min – Max |
|---|---|---|
| Race distance (km) | 22.20 ± 6.28 | 10.04–35.74 |
| Elevation gain (m) | 702.6 ± 312.1 | 245–1431 |
| Elevation gain per km (m·km$^{-1}$) | 30.86 ± 7.59 | 12.69–43.73 |
| Off-road terrain (%) | 79.3 ± 12.6 | 48–97 |
| Mean technicality level (0–10) | 2.66 ± 0.76 | 1.48–3.98 |
| Number of participants per race in the study | 25.7 ± 8.8 | 11–49 |
| **B. Segment Composition** | | |
| Proportion of uphill segments (%) | 31.99 ± 6.70 | 19.52–45.52 |
| Proportion of rolling segments (%) | 22.90 ± 12.94 | 0.00–49.50 |
| Proportion of flat segments (%) | 12.81 ± 11.33 | 3.50–49.51 |
| Proportion of downhill segments (%) | 31.74 ± 8.87 | 17.09–56.42 |
| **C. Participant Performance Level** | | |
| Be-Trail average score by race | 48.30 ± 2.23 | 44.31–53.32 |

have been specifically evaluated in standardised conditions, showing excellent reliability (ICC from 0.997 to 1) and very good validity (95% limit of agreement range from −3.86 to 3.35 sec) (De Cock et al., 2023). Additional research examining STRAVA-based activity tracking has reported satisfactory validity and usability in field settings (Porter et al., 2022). While GPS measurements may be influenced by satellite signal variability and environmental conditions, such effects are generally small relative to the terrain-related differences in segment speed examined in the present study. All data were anonymised prior to analysis. The protocol was approved by the Ethics Committee of the University of Liège (2022/211, 2023/243, 2024/179), and all participants provided informed consent for the use of their anonymised data.

### 2.2. Course segmentation and TSAT

Race courses were segmented using the Trail Segment Analysis Tool (TSAT), an original field-based framework designed to characterise trail courses and analyse runner performance at the segment level (De Cock et al., 2025). TSAT provides two complementary outputs: (1) a Trail Identity Card, summarising the structural characteristics of a course through standardised segmentation, and (2) a Trail Effort Analysis, which quantifies runners' performance across segments and provides the segment speed data used in the present study. Course segmentation was performed during on-site reconnaissance of each trail by members of the research team. A reference GPX track was recorded by the researchers during this reconnaissance and uploaded to the authors' STRAVA account. This track was used solely as a spatial reference to define course segments and to derive segment distance, elevation and mean slope using the STRAVA visualisation tools.

Natural transitions in slope, terrain, or surface were used to delineate segments, which were classified as uphill (mean gradient >+3%), downhill (mean gradient <−3%), flat (absolute gradient ≤3%), or rolling. Rolling segments corresponded to undulating or hilly sections characterised by frequent alternations of short ascents and descents exceeding ±3%, occurring over distances too short to be segmented individually as separate climb, descent, or flat sections. During this process, the technical difficulty of each segment was

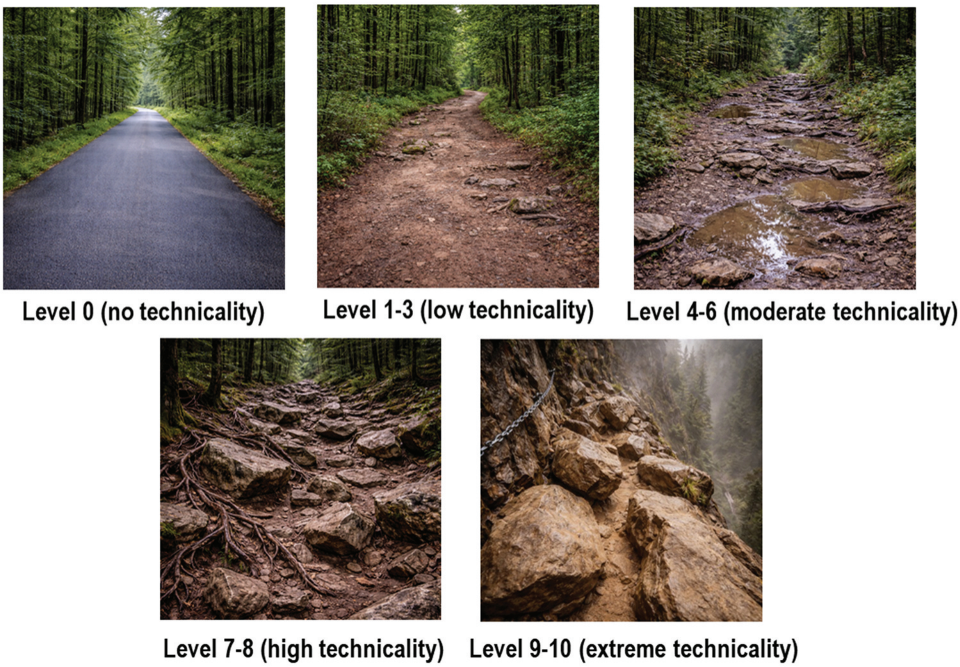
Level 0 (no technicality)
Level 1-3 (low technicality)
Level 4-6 (moderate technicality)
Level 7-8 (high technicality)
Level 9-10 (extreme technicality)

**Figure 1.** Illustrative examples of increasing technicality levels used for segment classification. Images were generated using artificial intelligence (ChatGPT, OpenAI).

rated on a 0–10 scale based on surface irregularity (e.g. presence of rocks, roots, uneven ground), obstacle density (e.g. natural barriers requiring step adjustment or avoidance), and footing stability (e.g. loose gravel, mud, slippery surfaces). This descriptor aimed to capture terrain characteristics likely to reduce running speed independently of slope. To illustrate the practical meaning of each score, representative visual examples of increasing technical difficulty levels were generated using artificial intelligence (ChatGPT, OpenAI) and are provided in Figure 1. Ratings were assigned during on-site reconnaissance by researchers trained in the TSAT methodology and experienced in trail running. This scale has undergone content validation through expert consensus (De Cock et al., 2025) but has not yet completed formal reliability or criterion validity testing. It was included to provide an exploratory quantification of terrain technicality in the absence of established objective measures.

TSAT was used in combination with participant-authorised performance data, visualised on the STRAVA platform, to manually retrieve individual segment times recorded during competition. All analyses were conducted outside the STRAVA platform. In total, 454 segments were identified and included in the analysis.

## 2.3. Variables

Segment-level performance was analysed using the average speed on each segment (SegSp, $m{\cdot}s^{-1}$). Each segment was characterised by its mean slope (SegSlope, %), horizontal length derived from the GPS track (SegLength, m), technical difficulty (SegTechn, 0–10), and position within the race (SegPos, expressed as the percentage of total race distance completed at the end of the segment). SegPos was included to account for race progression effects, capturing potential influences of global pacing strategy and fatigue that are not explained by local terrain characteristics alone. To account for overall race difficulty and the general performance level of participants, the average speed of runners across the entire trail (TrailAvSp, $\text{m}\cdot\text{s}^{-1}$) was included as a covariate in the analyses.

### 2.4. Statistical analysis

Descriptive analyses were first conducted to summarise segment characteristics. To determine the functional form of the relationship between segment speed (SegSp) and each predictor (SegSlope, SegTechn, SegLength, SegPos), simple regression analyses were first performed independently for each variable. Linear and polynomial models (second- and third-degree where theoretically justified, particularly for slope) were compared. Model selection at this exploratory stage was based on statistical significance of regression coefficients, adjusted $R^2$, and Akaike Information Criterion (AIC), allowing identification of the most appropriate functional form while avoiding unnecessary model complexity.

Variables and polynomial terms that significantly improved model fit were subsequently entered into a multiple linear regression model predicting SegSp. A stepwise comparison of nested models was conducted using adjusted $R^2$ and AIC to determine the most parsimonious model. Segment length was excluded from the final model as it did not significantly improve explanatory power when other predictors were included.

Basic diagnostic checks (residual distribution, homoscedasticity, multicollinearity) were examined to ensure adequacy of the final model. All analyses were performed using Statistics (version 13.5), with statistical significance set at $p < .05$.

## 3. Results

Descriptive characteristics of the segments, overall and by segment category, are presented in Table 2. Exploratory analyses indicated that the relationship between segment speed and slope (SegSp – SegSlope) was the strongest and followed a third-degree polynomial pattern (Figure 2; $R^2 = 0.69$, $p < 0.001$). Segment speed showed a weak negative linear relationship with technical difficulty (SegSp – SegTechn; $r = -0.19$, $p < 0.001$), and weak positive linear relationship with segment length (SegSp – SegLength; $r = 0.13$, $p$

**Table 2.** Segment characteristics, overall and by category. Mean ± sd (Min–max).

| Variable | All ($n = 454$) | Uphill ($n = 163$) | Rolling ($n = 78$) | Flat ($n = 72$) | Downhill ($n = 141$) |
|---|---|---|---|---|---|
| Segment Speed (SegSp in $\text{m}\cdot\text{s}^{-1}$) | 2.73 ± 0.63<br>(0.97–3.91) | 2.16 ± 0.51<br>(0.97–3.35) | 2.75 ± 0.42<br>(1.38–3.62) | 3.09 ± 0.29<br>(2.23–3.89) | 3.18 ± 0.43<br>(1.83–3.91) |
| Segment Length (SegLength in m) | 978 ± 628<br>(200–3920) | 861 ± 535<br>(200–3210) | 1369 ± 746<br>(430–3920) | 1041 ± 670<br>(320–3750) | 866 ± 544<br>(250–3160) |
| Segment Slope (SegSlope in %) | 0.7 ± 7.5<br>(−18.7–23.4) | 8.6 ± 4.4<br>(2.8–23.4) | 0.4 ± 1.9<br>(−4.7–3.8) | −0.1 ± 1.3<br>(−2.6–2.4) | −7.8 ± 3.1<br>(−18.7–−2.9) |
| Segment technicality (SegTechn 0–10) | 2.65 ± 1.81<br>(0–8.88) | 2.66 ± 1.98<br>(0–8) | 2.64 ± 1.58<br>(0–8.1) | 2.19 ± 1.61<br>(0–7) | 2.87 ± 1.78<br>(0–8.88) |

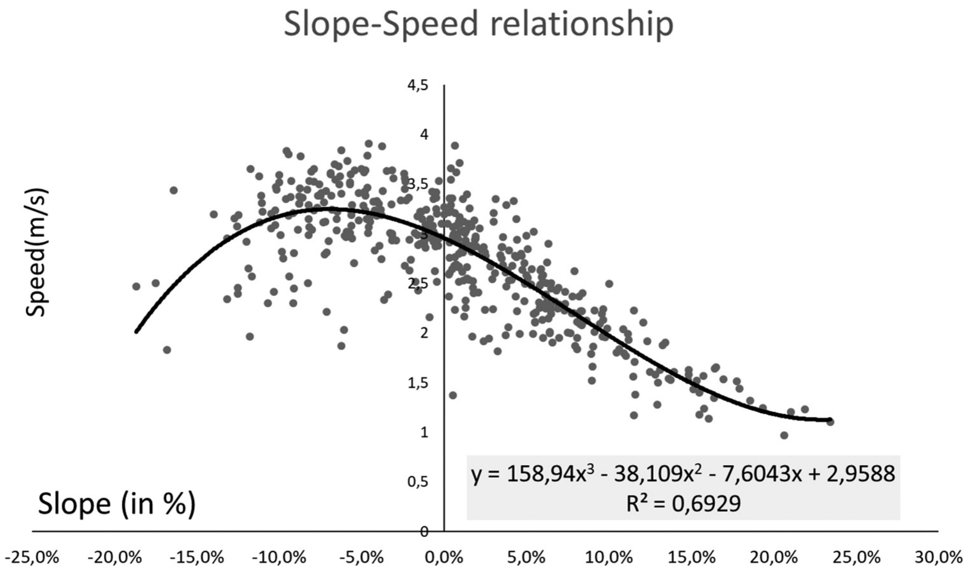

**Figure 2.** Relationship between segment speed (SegSp) and segment slope (SegSlope).

$< 0.01$). The association between segment speed and segment position in the race (SegSp – SegPos) was weak and best described by a second-degree polynomial function (Figure 3; $R^2 = 0.06$, $p < 0.001$). A moderate positive linear association was observed between segment speed and average trail speed (SegSp – TrailAvSp; $r = 0.38$, $p < 0.001$).

A multiple linear regression analysis was then performed to predict segment speed (SegSp) from segment characteristics and average trail speed. Two candidate models were compared: one including segment length and one excluding it. Although inclusion of

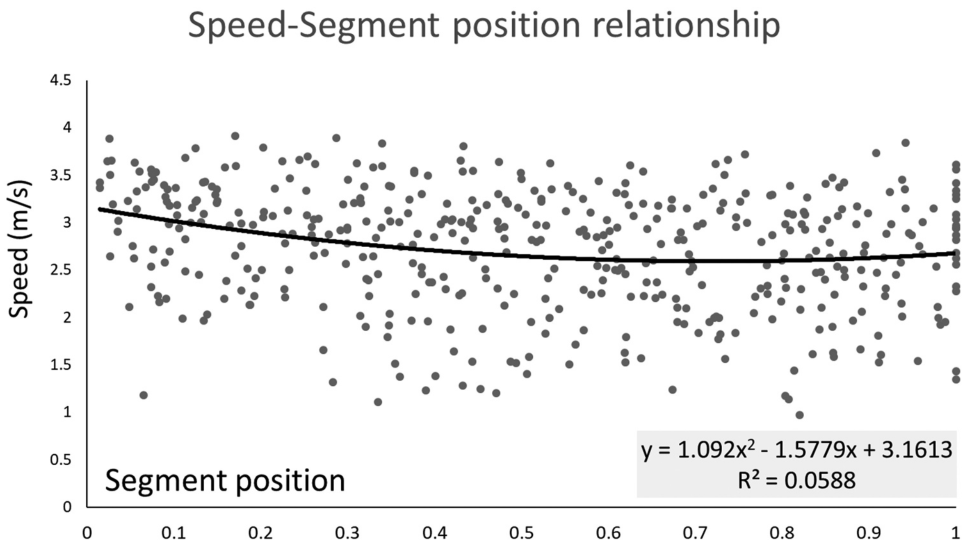

**Figure 3.** Relationship between segment speed (SegSp) and segment position (SegPos).

**Table 3.** Multiple regression model for segment speed (SegSp).

| | $R = .9014$; $R^2 = .8125$; Adjusted $R^2 = .8095$<br>F(7, 446)=276.05 $p < 0.000$ Std. Error of estimate: .27361 | | | | | |
|---|---|---|---|---|---|---|
| $N = 454$ | β | SE β | B | SE B | t | p-value |
| Intercept | | | 1.680 | 0.141 | 11.876 | 0.000 |
| TrailAvSp | 0.261 | 0.021 | 0.610 | 0.049 | 12.424 | 0.000 |
| SegSlope | −0.890 | 0.035 | −7.473 | 0.290 | −25.743 | 0.000 |
| $\text{SegSlope}^2$ | −0.384 | 0.026 | −30.704 | 2.092 | −14.677 | 0.000 |
| $\text{SegSlope}^3$ | 0.365 | 0.039 | 147.001 | 15.899 | 9.246 | 0.000 |
| SegTechn | −0.132 | 0.021 | −0.046 | 0.007 | −6.289 | 0.000 |
| SegPos | −0.345 | 0.085 | −0.760 | 0.185 | −4.098 | 0.000 |
| $\text{SegPos}^2$ | 0.188 | 0.085 | 0.382 | 0.173 | 2.208 | 0.028 |

Units: SegSp and TrailAvSp in $\text{m}\cdot\text{s}^{-1}$; slope in %; length in m; SegPos in % of race distance.

segment length slightly reduced the residual sum of squares (RSS = 37.603 vs. 37.606), model comparison based on the Akaike Information Criterion favoured the more parsimonious model without segment length (AIC = −1115.18 vs. −1113.23). Given the negligible improvement in model fit and the penalty for additional complexity, segment length was excluded from the final model. The retained model explained 81% of the variance in segment speed (Table 3). The final regression equation (1) was:

$$\text{SegSp} = 1.68 + 0.61 \cdot \ \text{TrailAvSp} - 7.473 \cdot \ \text{SegSlope} - 30.704 \cdot \ \text{SegSlope}^2 + 147.001 \cdot \ \text{SegSlope}^3 - 0.046 \cdot \ \text{SegTechn} - 0.760 \cdot \ \text{SegPos} + 0.382 \cdot \ \text{SegPos}^2 \tag{1}$$

## 4. Discussion

The data collected from short-distance trails and the use of the TSAT tool demonstrate that it is possible to gain deep insights into trail running performance using simple tools and field data, leveraging new technologies and applications. Our approach provides a robust model that explains 81% of the variance in the average speed on a segment, based on the runners' average speed across the race and three significant segment characteristics: slope, technical difficulty, and position in the race. This level of predictive power is noteworthy as it provides a practical tool for segment-level performance analysis. Coaches and athletes may use the model to estimate expected split times based on course profile prior to competition, to identify segments where pacing deviates from predicted values, and to better distribute effort according to terrain characteristics. In addition, practitioners can use this framework to benchmark performance across races with different profiles by adjusting for slope, technicality, and race position. Such applications may support individualised pacing strategies and more informed race preparation in trail running contexts. This method allows for relatively accurate predictions of expected split times per segment and can help identify discrepancies between these predictions and the actual time.

The present findings clearly identify slope as the primary determinant of segment speed in trail running. The observed third-degree polynomial relationship for speed is consistent with the fundamental energetics of locomotion established in laboratory settings (Lemire et al., 2021; Minetti et al., 2002). While our model is derived from field data collected during real competitions, the characteristic shape of the relationship (i.e. showing a rapid decrease in speed on steep uphills, maximal speeds on moderate downhills around −8%, and a subsequent decrease on steeper declines) closely mirrors patterns reported under laboratory conditions (Dewolf & Willems, 2019; Minetti et al., 2002). Importantly, this consistency across markedly different contexts (controlled laboratory experiments involving highly trained runners versus real-world pacing data from more recreational participants) suggests that the influence of slope on running speed appears to be largely independent of performance level or environmental conditions. This agreement suggests that running speed in trail environments remains strongly constrained by energetic demands, despite the added complexity of real-world conditions. The specific gradient for optimal speed observed in our field data (~−8%) is in close agreement with the value predicted by biomechanical models for minimising energetic cost (Dewolf & Willems, 2019). This convergence between laboratory-based and field-based observations reinforces the idea that running speed in real-world trail settings is fundamentally constrained by energetic demands. Runners tend to achieve their highest speeds at gradients where the metabolic cost of locomotion is lowest, reflecting the physiological limits imposed by terrain. On steeper descents beyond approximately −15%, the increase in mechanical braking forces and the reduced control required for stability overall lead to a pronounced loss of speed, despite the assistance of gravity (Vernillo et al., 2017). In this respect, the present study extends previous laboratory findings by demonstrating that the speed – slope relationship persists under competitive conditions, where additional factors such as fatigue (race progression) and terrain technicality interact with running speed. Recent advances in wearable technologies have enabled the estimation of energetic demand during running in variable terrain (Gravina-Cognetti et al., 2025; Mason et al., 2023). However, these approaches require additional hardware, calibration, and user compliance, which may limit their applicability in large-scale or retrospective analyses. In contrast, the present approach relies solely on widely available GPS recordings and course elevation data, offering a complementary and accessible framework to capture terrain-related constraints on running performance under real-world conditions.

Our model also shows that speed decreases linearly as the technical difficulty of the segment increases. Although the contribution of this variable was weaker than that of slope, its inclusion provides novel insight into how terrain complexity may influence running behaviour in trail environments. To our knowledge, this is the first study to incorporate this variable quantitatively into a predictive speed model. This finding is strongly supported by the biomechanical research showing that running on irregular or unstable surfaces (e.g. rocks, roots, uneven ground) requires substantial gait adaptations to maintain balance and safety (Giandolini et al., 2015; Mohr et al., 2023). Runners must dynamically adjust foot placement, which leads to a more cautious, crouched gait pattern with increased leg flexion and higher stride-to-stride variability (Giandolini et al., 2015; Mohr et al., 2023). These adaptations, such as increasing frontal plane foot angle and decreasing knee flexion to manage surface unpredictability (Gantz & Derrick, 2018), inherently increase metabolic cost and reduce running economy (Voloshina & Ferris, 2015). Furthermore, the need for visual regulation to secure proper footing diverts cognitive resources and further contributes to a slower, more controlled pace (Hwang et al., 2024; Warren et al., 1986). Therefore, the observed speed reduction on technical segments likely reflects the combined influence of higher energetic demands and more cautious pacing behaviour to mitigate injury risk.

However, the relatively modest contribution of technicality in our model cannot be explained by a lack of demanding terrain. Despite a moderate average technicality (≈1.5–4/10 on the scale), the dataset included a meaningful proportion of highly technical segments ($49/454 \geq 5/10$; max = 8.88), indicating that such conditions were effectively represented. Rather, these findings suggest that the influence of technicality on running speed may be context-dependent rather than strictly linear. Its impact may be more pronounced under specific conditions, such as steep descents or higher running speeds, where biomechanical constraints, stability requirements, and risk management become critical. Within this framework, technicality contributes to speed regulation but remains secondary to slope as the primary determinant of segment performance.

At the same time, the characteristics of the present dataset should be considered when interpreting these findings. The races analysed were short-distance events conducted in hilly, non-mountainous environments, and involved predominantly recreational runners. In such a context, slope may dominate speed regulation, whereas the influence of technical terrain may differ in more demanding trail environments (e.g. highly technical or mountainous races).

Another limitation of our study is that the measurement of technicality was performed using a perceived technicality scale during course reconnaissance and remains subjective (De Cock et al., 2025). This scale is recent and has not yet undergone full validation; further work is needed to confirm its scientific reliability and objectivity, potentially by correlating it with quantitative measures of terrain irregularity. Consequently, the observed relationship should be interpreted as exploratory rather than causal. The relatively small effect size may reflect both the multifactorial nature of trail running performance and current methodological limitations in objectively quantifying terrain technicality. It may also reflect the presence of additional unmeasured contextual factors influencing segment speed. Nevertheless, these findings highlight the potential relevance of technical terrain as a performance constraint and underscore the need for future research to develop validated, objective measures of trail technicality.

Segment speed was also significantly associated with segment position in the race, as reflected by the retained linear and quadratic SegPos terms in the regression model. On average, speed showed a gradual decline across the early and mid-portions of the race, followed by a slight increase towards the final segments. This pattern may reflect a combination of accumulating physiological strain and pacing regulation. Reductions in running pace over prolonged efforts have been associated with physiological fatigue, as increases in markers of muscle damage correlate with pace decline during marathon running (Del Coso et al., 2013), and neuromuscular fatigue has been proposed as an important determinant of endurance running strategies (Millet, 2011). The late-race increase in speed observed in the present study resembles the well-documented “end-spurt” phenomenon reported in road and trail races, where runners transiently increase effort as they approach the finish line (Hoffman, 2014; Sha et al., 2024). This is consistent with contemporary pacing models in which runners regulate speed based on physiological state and anticipated remaining demands. Field studies in trail running further show anticipatory pacing adjustments according to terrain and race context (de Waal et al., 2025; Jaén-Carrillo et al., 2025). Therefore, the segment position effect observed here likely reflects an interaction between race progression and pacing regulation.

However, the relatively modest contribution of segment position in our model may be partly explained by the characteristics of the studied population and race format, as pacing variability has been shown to depend on both race duration and runner characteristics (Cuk et al., 2021; Hoffman, 2014; Tan et al., 2016). The races analysed were relatively short and involved predominantly recreational runners, for whom pacing strategies may be more heterogeneous and less tightly regulated than in higher-level athletes. This variability may attenuate the overall relationship between race position and speed at the group level. In contrast, more pronounced and structured pacing effects might be expected in longer races or among more competitive runners.

The average speed of the runners over the entire trail (TrailAvSp) also has a very significant, positive influence on the speed in each segment. This variable likely reflects overall performance capacity and, to some extent, the global difficulty of the race context. In endurance running, mean race velocity is closely associated with aerobic fitness and performance level (Joyner & Coyle, 2008). Including this simple parameter allows for a more straightforward and robust model by controlling for these overarching factors, focusing the analysis on the relative impact of segment-specific characteristics.

Taken together, these findings indicate that segment speed in trail running emerges from the interaction between global performance level and local terrain constraints.

The strengths of this analysis lie in the originality of the approach and the novel possibility of extracting field data to better understand performance and model segment speed based on its characteristics. Although GPS-derived measures may be influenced by satellite signal variability and environmental conditions, their validity and reliability have been previously investigated and were considered sufficient for the purposes of the present field-based analysis (De Cock et al., 2023; Johansson et al., 2020; Porter et al., 2022). While some measurement variability cannot be entirely excluded, such variability is unlikely to account for the strong terrain-related effects observed in the present study. A limitation is that this analysis is based exclusively on short-distance trails in the specific context of Belgium, which features hilly terrain with moderate average technical difficulty, but is not mountainous. In addition, the participant sample was predominantly composed of recreational runners. These races are therefore not representative of all trail running events, and further research is needed to verify if this approach is applicable to other contexts (e.g. alpine environments, ultra-distance races). In particular, the relative influence of slope and technicality may differ in more demanding environments, such as highly technical or mountainous races, and among higher-level or elite runners.

A methodological consideration is that segment-level data were accessed via a commercial platform; however, all data were participant-authorised and processed independently of the platform.

The present model provides practical applications for athletes and coaches by enabling estimation of expected segment speeds based on course characteristics and overall performance level. Such predictions may assist in pre-race pacing planning, identification of terrain-specific strengths or weaknesses, and post-race performance analysis by comparing predicted and realised segment speeds. Beyond pacing strategy, this approach also offers a framework to better understand contextual factors that may influence running speed in competition. For example, deviations between predicted and actual segment speeds may help identify the impact of external constraints such as trail congestion, bottlenecks in narrow sections, or time spent at aid stations. In this way, the model may contribute not only to performance optimisation but also to a more comprehensive understanding of the determinants of speed variation in trail running. Future work should focus on validating the model in diverse trail environments, refining the technicality scale, and exploring integration into decision-support or pacing tools.

## 5. Conclusion

This study presents a field-based model for predicting segment pace in short-distance trail running events involving predominantly recreational runners and low-to-moderate technical terrain, explaining 81% of the variance in segment speed. Slope emerged as the dominant determinant, exhibiting a cubic relationship with speed and confirming maximal values on moderate downhills (~−8%) followed by marked reductions on steeper gradients. Technical difficulty and segment position within the race also contributed significantly, although to a lesser extent. Within this specific context, these findings highlight how local terrain characteristics interact with overall performance level to shape pacing behaviour in trail running. The proposed approach provides a practical framework for athletes, coaches, and performance analysts to estimate expected segment speeds, evaluate terrain-specific performance demands, and compare predicted versus actual pacing using accessible GPS-derived data. However, the relative influence of technicality and race position may differ in more competitive populations and in longer or more technical trail events, where pacing dynamics and terrain constraints are likely to be more pronounced. Future research should examine the applicability of this model in more diverse contexts, including mountainous and longer-distance events, and focus on developing objective measures of trail technicality.

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## Author contributions

CRediT: **Boris Jidovtseff:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Writing – original draft, Writing – review & editing; **Florence De Cock:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Validation, Writing – review & editing.

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## Use of artificial intelligence (AI) tools

Artificial intelligence (AI) tools were used during the preparation of this manuscript in accordance with the Taylor & Francis AI Policy. The original manuscript was written entirely in French by the authors. Generative AI tools (ChatGPT (version GPT-5, OpenAI, 2025) and DeepL) were used to assist with translation into English and to improve clarity, wording, and adherence to journal style requirements. All content, conceptual development, and scientific interpretation remain the full responsibility of the authors. The final manuscript was carefully reviewed and edited to ensure accuracy, originality, and integrity.

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