

Decoding speed climbing: AI-powered biomechanical analysis of elite performance

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Abstract:

This study explores the biomechanical factors that affect speed climbing performance using advanced AI-based motion analysis. Design: A retrospective analysis was performed using video recordings from 11 international competitions (2017–2023), focusing on three top athletes with the highest number of performances ($n = 56$). Methods: A computer vision system with a convolutional neural network enabled markerless motion analysis, to extract key kinematic parameters, including as center of gravity trajectory, contact times, limb frequency, and flow parameters. Multiple regression analyses with backward elimination identified significant predictors of End Time, using a significance threshold at $p < 0.05$. Results: Significant correlations were found between hand limb frequency measures and End Time across all athletes ($r = 0.437$ – 0.640 , $p < 0.001$). Regression analysis revealed athlete-specific predictors: Limb Frequency was the strongest predictor for Athlete 1 ($\beta = 0.900$), while Athlete 2's performance was influenced by overall limb frequency ($\beta = -0.625$) and maximum foot load ($\beta = 0.638$). Athlete 3 demonstrated an alternative strategy characterized by rapid foot transitions and consistent hand movement rhythm. Analysis of contact times showed that Athlete 2 had the shortest average hand contact time (0.35 ± 0.087 s), indicating superior efficiency in hand repositioning. Athlete 1 exhibited anomalies in foot contact parameters, including a notably long minimum foot contact time, potentially reflecting technical inefficiencies or variability in movement execution. Athlete 3 performed closest to the group average but showed greater consistency across trials. Multicollinearity issues highlighted the interdependence of biomechanical parameters, emphasizing the need for advanced analytical approaches. Conclusions: Speed climbing performance is characterized by distinct athlete-specific patterns, underscoring the importance of personalized training methodologies. The study demonstrates the potential of AI-driven systems for detailed biomechanical analysis, while also highlighting the need for future research incorporating larger datasets, longitudinal designs, and physiological measures to provide a more comprehensive understanding of speed climbing performance determinants.

Key Words: Speed climbing, Biomechanics, AI motion analysis, Performance predictors, Computer vision, Sport climbing, Rock climbing, AI in sport, artificial intelligence

Introduction

Sport climbing is a physically and technically demanding discipline that combines strength, endurance, flexibility, and precise neuromuscular control to overcome artificial or natural rock surfaces (Deyhle et al., 2015). The sport requires climbers to execute complex movement sequences under conditions of high physical load and mental concentration, making it a unique integration of physiological and cognitive challenges (MacKenzie et al., 2019). Since its official recognition as a competitive sport, climbing has evolved into three distinct disciplines: lead climbing, bouldering, and speed climbing, each with specific performance requirements and technical characteristics (Watts, 2004). The inclusion of sport climbing in the Olympic Games since Tokyo 2020 has significantly increased scientific and coaching interest in understanding the biomechanical, physiological, and psychological factors underlying elite performance. These developments have prompted a growing need for advanced analytical methods to objectively assess and optimize athletic performance across all climbing modalities (Walker et al., 2020).

The study of biomechanics in climbing is essential for advancing both scientific understanding and practical training methodologies (Saul et al., 2019). Biomechanical analysis allows researchers and coaches to quantify movement efficiency, identify technical flaws, and optimize performance by linking specific kinematic and kinetic parameters to competitive outcomes (Fisher et al., 2021). In speed climbing, where differences of hundredths of a second determine victory, even minor improvements in movement economy—such as reduced hand contact time or optimized limb coordination—can have decisive impacts (Levernier et al., 2020). By analyzing parameters like center of gravity trajectory, contact durations, and limb frequency, biomechanics provides objective metrics that go beyond subjective observation, enabling precise feedback and targeted intervention (Noe et al., 2001).

Speed climbing is a unique discipline in competitive climbing that demands specialized skills and a high degree of accuracy. Unlike lead climbing or bouldering, it focuses on achieving maximum speed as athletes race up a standardized 15-m wall with identical holds and route designs (Shulga, 2010). This discipline requires explosive lower-body strength, accurate footwork, and quick decision-making. The uniformity of the routes enables direct head-to-head competition, increasing its appeal to spectators. Its inclusion in the Olympic Games underscores the increasing importance of speed climbing in competitive sports (Lutter et al., 2021). Speed climbing exhibits distinct biomechanical features where increased speed correlates with higher finger reaction forces, more pronounced initial contact shock spikes, and shorter hold contact times. The force-velocity relationship tends to plateau at higher speeds, which helps reduce injury risk, whereas shock spikes increase linearly with velocity. Climber experience significantly influences performance, and more skilled athletes generate greater forces and spend less time on holds. These dynamic force application patterns set speed climbing apart from other climbing disciplines (Fuss & Niegl, 2006).

Technical climbing skills are essential for professional climbers, especially in speed climbing, where movement efficiency directly affects performance. Elite speed climbers exhibit significantly greater explosive strength and muscle activation compared to recreational climbers (Krawczyk et al., 2018). These technical abilities are evident in accurate footwork, optimal body positioning, and effective energy use during climbs. Research highlights that professional climbers' superior technical skills enable more efficient execution of movement sequences such as step-reach-step. Importantly, success in speed climbing relies mainly on high-intensity, short-duration strength rather than flexibility or basic somatic characteristics, underscoring the importance of specialized technical training for peak performance (Krawczyk & Ozimek, 2014).

Previous research by Legreneur explores the capture of speed climbing technique using video recordings taken at 30 Hz with a stabilized camera positioned 4.5 m high and 14 m from the wall. The geometric entropy index was significantly lower in males (0.103 ± 0.032) than in females (0.140 ± 0.056), indicating smoother movement in males. Analysis of body mass center (BMC) velocity showed considerable decreases throughout the route, more pronounced in females (-0.53 ± 0.18) than males (-0.39 ± 0.23). Performance differences were mainly attributed to males' ability to reduce lateral movements, sustain higher velocity during acceleration phases, and better control speed after dynamic moves. These findings provide valuable insights into biomechanical factors influencing speed climbing performance.

Another study used advanced 3D visualization techniques to analyze body motion in speed climbing using drone-captured video and markerless video-based tracking systems. A 3D avatar of the climber was generated in a laboratory studio with 68 cameras, allowing detailed motion capture through manifold learning for 3D shape analysis. The findings revealed significant differences between traditional harness-mounted marker trajectories and the estimated center of mass (COM) positions obtained from the 3D mesh model. On average, the differences between the marker and 3D mesh COM were 7.3 ± 5.9 cm laterally (X direction), 8.7 ± 4.6 cm vertically (Y direction), and 24.1 ± 4.3 cm perpendicular to the wall (Z direction). The greatest discrepancy occurred in the Z direction, caused by limb projections toward the wall that the harness marker failed to capture. During critical "dyno" movements, the 3D mesh COM estimation was more accurate, especially when the legs were flexed upward, showing vertical differences up to 16.1 cm compared to the marker.

Our previous studies were aimed at analyzing the competitive technique of rock climbers based only on physiological characteristics and observations, which showed the results and prospects for further research into the biomechanics of movements in speed climbing (Shunko et al., 2020). We also conducted studies of the physical fitness of climbers in speed climbing, which showed high significance, but left sufficient gaps to justify the need to study the detailed biomechanics of movements (Shunko, 2025).

Speed climbing is a highly specialized discipline within competitive climbing, characterized by maximal velocity and precise movement execution on a standardized route (Ryepko, 2013). Despite its inclusion in international competitions, including the Olympic Games, the biomechanical determinants of performance in speed climbing remain insufficiently understood. Previous studies have highlighted the importance of technical skills, explosive strength, and movement efficiency; however, most analyses have relied on traditional motion capture methods with limited ecological validity or small, heterogeneous samples (Pongsiri et al., 2022). The existing body of research lacks a comprehensive, athlete-specific approach that accounts for the complex interplay of biomechanical variables influencing performance. Moreover, conventional statistical methods often fail to capture nuanced movement patterns due to multicollinearity and inter-individual variability (Kozina et al., 2020). Therefore, there is a clear need for advanced analytical tools, such as AI-powered motion analysis, to provide more accurate and detailed insights. This study addresses the gap by employing a markerless computer vision system combined with regression modeling to identify key predictors of performance. By focusing on elite athletes and utilizing retrospective competition data, the research aims to enhance understanding of speed climbing biomechanics and inform personalized training strategies for optimal performance outcomes.

Material & methods

To identify climbing parameters, we use a computer vision system for motion analysis called Athlete AI (Pandurevic et al., 2023). This system was developed to analyze the movements of competitive speed climbers through video recordings. It uses a convolutional neural network to recognize human body joints, removing the

need for physical markers on the athletes. Custom algorithms then calculate key kinematic parameters, including center of gravity (COG) position and trajectory, velocity and acceleration profiles, contact times for hands and feet, flow parameters, and limb frequency.

The videos used in this study were obtained from recordings of 11 competitions held between 2017 and 2023, provided by the International Federation of Sport Climbing (IFSC), with a frame rate of 25 FPS. From these, we selected 3 athletes with the highest number of performances, resulting in a total analysis of 56 performances.

Multiple regression analysis was performed using the backward elimination method, with entry and removal thresholds set at $p < 0.05$ and $p > 0.10$, respectively. The dependent variable was End time, while independent variables included Contact times for hands and feet, Flow parameters, and Limb Frequency (Figure 1). Descriptive statistics, such as the mean and standard deviation, were calculated for both dependent and independent variables. ANOVA assessed the overall significance of the regression model, reporting explained variance through the sum of squares, degrees of freedom, mean square values, and F-statistics. Statistical significance for all tests was established at $p < 0.05$. Descriptive statistics were calculated for all variables, including measures of central tendency (mean) and dispersion (standard deviation). Spearman's rank correlation coefficient (ρ) was used to evaluate the strength and direction of associations between variables. Means and standard deviations were also calculated for each variable to characterize the sample. Statistical and graphical analyses were performed using SPSS Statistics and PrismGraph.

Results

Descriptive analysis

The initial statistical analysis indicated no apparent differences in the athletes' results across all parameters (Table 1). However, biomechanical metrics show that Athlete 2 outperforms Athletes 1 and 3, especially in "End time" and "Contact time avg Hand," where shorter times reflect greater efficiency. Despite this, Athlete 2 also exhibits significant variability in certain measures, such as a high standard deviation in "Contact time max Feet," suggesting possible inconsistencies in foot movement mechanics. In contrast, Athlete 1 exhibits anomalies in foot-related parameters, such as an unusually long minimum foot contact time and increased variability in maximum foot contact time, which may indicate inefficiencies or measurement errors. Athlete 3, meanwhile, performs closest to the group average in most parameters, showing consistent but less outstanding results. Overall, although Athlete 2 achieves the best mean values, the greater variability in specific metrics suggests the need for further investigation to confirm performance stability.

Table 1. Descriptive statistics of artificial intelligence (AI)-based analysis results

	All (n=56)		Athlete 3 (n=17)		Athlete 2 (n=19)		Athlete 1 (n=20)	
	$\bar{x}$	σ	$\bar{x}$	σ	$\bar{x}$	σ	$\bar{x}$	σ
End Time, s	5,1	,16	5,06	,21	5,12	,140	5,12	,13
Contact time, s	,39	,08	,41	,05	,35	,08	,40	,11
Contact time min Hand, s	,23	,03	,23	,03	,23	,037	,23	,04
Contact time max Hand, s	,66	,26	,80	,25	,55	,22	,66	,25
Contact time avg Hand, s	,38	,07	,39	,04	,35	,087	,40	,073
Contact time min Feet, s	,72	3,71	,22	,02	,22	,029	1,61	6,21
Contact time max Feet, s	1,12	4,75	2,53	8,62	,43	,24	,56	,33
Contact time avg Feet, s	,3	,04	,30	,02	,29	,03	,31	,06
Limb frequency, s	1,58	,24	1,62	,08	1,53	,34	1,61	,21
Limb frequency min Hand ,s	1,07	,11	1,06	,05	1,04	,11	1,11	,14
Limb frequency max Hand, s	3,21	,6	3,43	,60	3,35	,63	2,89	,43
Limb frequency med Hand, s	1,81	,19	1,83	,11	1,82	,21	1,77	,23
Limb frequency min Feet, s	,94	,10	,92	,05	,95	,14	,95	,1
Limb frequency max Feet, s	2,19	,37	2,11	,16	2,15	,42	2,28	,45
Limb frequency med Feet, s	1,37	,18	1,34	,04	1,35	,20	1,42	,21
Flow parameter, s	,32	,15	,34	,18	,28	,16	,33	,12
Flow parameter hand, s	,22	,16	,25	,2	,19	,12	,23	,15
Flow parameter feet, s	,23	,15	,23	,15	,23	,16	,24	,15

Correlation analysis

A Pearson correlation analysis was performed to explore the relationships between End time and various climbing performance parameters. The results showed several significant findings. End time had a weak positive correlation with Contact time ($r = 0.107$, $p = 0.432$), but this was not statistically significant. Similarly, Contact time min Hand ($r = -0.107$, $p = 0.433$) and Contact time max Hand ($r = 0.159$, $p = 0.242$) also exhibited weak, non-significant correlations with End time. However, among limb frequency measures, End time demonstrated moderate positive correlations with Limb frequency min Hand ($r = 0.569$, $p < 0.001$), Limb

frequency max Hand ($r = 0.640$, $p < 0.001$), and Limb frequency med Hand ($r = 0.437$, $p = 0.001$), all of which were statistically significant.

These findings indicate that longer completion times are related to higher frequencies of hand movements. The correlation between End time and FlowParR2 was weak and not statistically significant ($r = 0.147$, $p = 0.281$). Similarly, the relationships with Flow parameter hand ($r = -0.036$, $p = 0.794$) and Flow parameter feet ($r = 0.193$, $p = 0.154$) were also non-significant. Additionally, End time showed weak negative correlations with Contact time avg Hand ($r = -0.036$, $p = 0.794$) and Contact time min Feet ($r = -0.044$, $p = 0.750$), but these associations did not reach statistical significance.

These findings suggest that End time is mainly related to hand movement frequency characteristics in climbing performance, showing limited connections with other measured parameters. The strongest associations were found between End time and various hand frequency metrics, indicating that these factors are particularly important for climbing time performance.

Regression analysis

To gain deeper insights into the factors affecting the End time for each athlete, performing a regression analysis based on their individual performance metrics is essential. This analysis helps identify key predictors driving variations in End time, offering a clearer understanding of each athlete's unique biomechanical and physiological traits. Parameters such as Contact time avg Hand, Limb frequency, and Flow parameter may influence End time differently among athletes, reflecting their specific movement patterns and efficiencies. By isolating these relationships through regression modeling, we can determine which variables most strongly correlate with faster or slower End time values for each individual.

A backward multiple regression analysis was performed to examine the relationship between various biomechanical parameters and the climbing performance (End time) of each athlete.

Athlete 1

The standardized and unstandardized coefficients for predictors in Athlete 1's final model show Limb frequency with the highest standardized coefficient ($\beta = 0.900$), indicating that it is the strongest predictor of End time. Other significant predictors are Contact time ($\beta = 0.546$), Contact time max Hand ($\beta = -0.459$) as shown in Figure 2, and Contact time avg Feet ($\beta = 0.360$). The constant term ($B = 5.839$, $SE = 0.000$) is also statistically significant, but its interpretation is limited owing to the model's perfect fit.

Collinearity statistics revealed potential multicollinearity concerns, highlighted by a tolerance value of 0.000 for the excluded variable Contact time min Feet. This indicates that some predictors are highly correlated, requiring caution when interpreting their individual effects. Additionally, the residuals' standard deviation was 0.000, confirming no unexplained variability in the model. Standardized predicted values ranged from -1.161 to 1.709 .

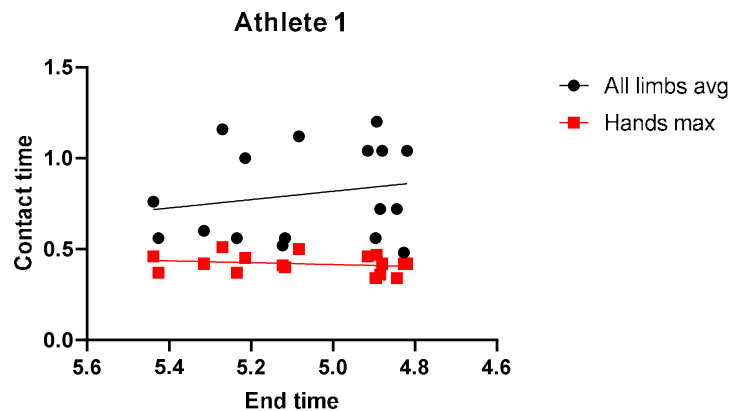


Fig. 1. Relationship Between Contact Time and End Time for Athlete 1

Athlete 2

The backward elimination process for Athlete 2 yielded a final model with two significant predictors: Limb frequency ($\beta = -0.625$, $p = 0.024$) and Limb frequency max Feet ($\beta = 0.638$, $p = 0.021$) (Figure 3). This simplified model accounted for 33.7% of the variance in End time (Adjusted $R^2 = 0.254$). The ANOVA for the model was significant, $F(2,16) = 4.058$, $p = 0.038$, confirming that together Limb frequency and Limb frequency max Feet significantly predicted End time. The standardized coefficients indicate that higher limb movement frequency and greater maximum foot load were related to improved climbing performance.

Model diagnostics showed that the residuals were normally distributed with a mean of 0.000 and a standard deviation of 0.114. Predicted values ranged from 5.0105 to 5.3753 s, with a mean of 5.1223 s ($SD = 0.08124$).

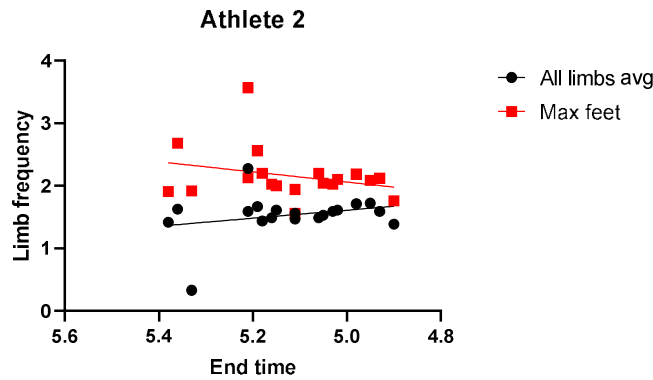


Fig. 2. Relationship between Limb frequency and End time for Athlete 2

The stepwise removal of non-significant predictors improved the model fit, demonstrated by the adjusted R² increasing from negative values in the initial models to 0.254 in the final model. Additionally, variance inflation factors for all retained predictors remained below 2, indicating no multicollinearity concerns.

Athlete 3

The initial model for Athlete 3, including all 17 predictors, showed a high R-squared of 0.920 but a low adjusted R-squared of 0.241 ($F(17,2) = 1.355$, $p = 0.507$). As variables were removed, the adjusted R-squared improved, peaking at step 12 with a value of 0.338 ($F(11,8) = 2.106$, $p = 0.126$).

The final model retained two predictors—Contact time min Feet and Limb frequency med Hand—and demonstrated statistical significance ($F(2,17) = 4.326$, $p = 0.030$), with R-squared = 0.337 and adjusted R-squared = 0.259. Both predictors made significant individual contributions ($p < 0.05$).

Residual analysis confirmed that residuals were normally distributed (mean = 0.00000, SD = 0.11164), and standardized residuals ranged from -1.804 to 2.310, indicating no major violations of regression assumptions.

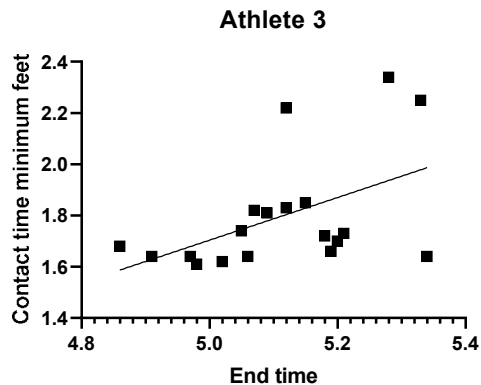


Fig. 3. Relationship Between Contact Time (Minimum Feet) and End Time for Athlete 3

These results suggest that, among the initial set of variables, only Contact time min feet t (Figure 4) and Limb frequency med hand remained significant predictors of End time after controlling for other variables in the model.

All Athletes

The initial model, including all athletes and 17 predictors, yielded an R² of 0.406. As variables were sequentially eliminated based on a significance threshold of $p > 0.10$, the adjusted R² values gradually improved, reflecting increased model efficiency. Although the R² decreased from 0.406 in the initial model to 0.262 in the final model, the adjusted R² peaked at 0.204 in Model 14. This indicates that the final set of four predictors explains approximately 20.4% of the variance in End time.

The ANOVA results showed that all models except the first three were statistically significant ($p < 0.05$). F-values gradually increased from Model 4 ($F = 1.979$, $p = 0.045$) to Model 14 ($F = 4.526$, $p = 0.003$), indicating improved explanatory power despite fewer predictors.

Standardized coefficients revealed that Contact time max Hand had the strongest negative association with End time across several models (β between -0.442 and -0.498, $p < 0.01$). Contact time avg Feet consistently had positive associations ($\beta \approx 0.42$, $p < 0.01$), and Contact time min Feet showed significant positive effects in later models ($\beta \approx 0.28$, $p < 0.05$).

Residual analysis confirmed assumptions of normality and homoscedasticity, with standardized residuals ranging from -1.934 to 1.866 and a mean of zero. The final model's low standard error of estimate (0.08419) indicates good predictive accuracy.

Dicussion

Our analysis revealed distinct patterns in the relationship between various performance metrics and completion time (End time) across the three athletes, indicating the potential for individual-specific optimization strategies in speed climbing technique.

The significant correlation between hand limb frequency measures and End time (ranging from $r = 0.437$ to $r = 0.640$, $p < 0.001$) supports earlier findings that highlight the essential role of upper body dynamics in speed climbing [3]. Athlete 2 exhibited greater performance efficiency, as reflected in an optimized average hand contact time (0.35 ± 0.087 s), which was significantly lower than the group mean (0.38 ± 0.07 s). Regression analysis revealed distinct athlete-specific predictors of performance. For Athlete 1, Limb Frequency All was the strongest predictor ($\beta = 0.900$), explaining a substantial portion of the variance in End time. This supports Legreneur's findings on the importance of movement fluency in improving speed climbing performance. In contrast, Athlete 2's performance was mainly determined by a combination of overall limb frequency ($\beta = -0.625$, $p = 0.024$) and maximum foot load ($\beta = 0.638$, $p = 0.021$), accounting for 33.7% of the variance in End time. The analysis of Athlete 3 revealed a unique pattern, with minimum foot contact time and median hand limb frequency emerging as significant predictors. This suggests an alternative technical strategy characterized by rapid foot transitions and a consistent hand movement rhythm. These findings align with previous research indicating that successful speed climbing techniques can differ among individuals while still achieving high performance levels. The multicollinearity issues identified in our models, especially for Athlete, underscore the complex interrelationships between biomechanical parameters in speed climbing. These findings suggest that traditional isolated parameter analysis may be inadequate for a comprehensive evaluation of performance, highlighting the need for more advanced analytical approaches such as the artificial intelligence (AI)-based systems used in this study. Our results emphasize the importance of analyzing both temporal and spatial parameters in performance evaluation. The significant relationships observed between various contact times and End time—particularly CTmaxHand, with β values ranging from -0.442 to -0.498 ($p < 0.01$ across all athletes)—confirm the importance of accurate timing in hold engagement and release during speed climbing.

Although the study provides valuable biomechanical insights, certain limitations should be noted. The relatively small sample size (56 performances) and focus on only three elite athletes may limit the broader applicability of the findings. Future studies with larger, more diverse climber populations are needed to validate and extend these results. These findings have practical implications for coaching methods and training program design in competitive speed climbing. Identifying key performance predictors tailored to individual athletes indicates that personalized training strategies may be more effective than uniform protocols. Additionally, the study's successful use of computer vision systems highlights the promising role of AI technology in enabling detailed and accurate performance analysis in climbing sports.

Limitations

First, the relatively small sample size, especially when analyzed by individual athletes, may reduce statistical power and increase the likelihood of errors in detecting significant relationships between performance variables. Second, the cross-sectional design of this study limits our ability to establish causal relationships between biomechanical parameters and performance outcomes. Performing longitudinal research that tracks athletes over time would offer stronger evidence on how speed climbing techniques develop and influence performance metrics.

Third, although our AI-based computer vision system provides advanced motion analysis, the lack of direct force measurement devices limits our ability to accurately quantify ground reaction forces and joint kinetics. Future studies incorporating force platforms or wearable sensors would increase the biomechanical insights. Moreover, the 25 FPS video recording rate, while sufficient for basic motion analysis, may overlook subtle details of the rapid, dynamic movements typical of elite speed climbing. Using higher frame rates along with multiple camera angles would improve the accuracy of kinematic assessments.

Finally, by focusing only on technical parameters without including physiological measures such as muscle activation patterns or metabolic responses, the study presents an incomplete understanding of the factors influencing speed climbing performance. Incorporating these physiological markers in future research would provide a more comprehensive and holistic insight into the demands of the sport.

Conclusions

Our findings demonstrate that speed climbing performance, especially regarding completion time (End time), involves distinct, athlete-specific patterns and predictors. The analysis showed strong correlations between hand limb frequency measures and End time for all athletes, highlighting the importance of upper body dynamics in speed climbing success.

Notably, regression analysis revealed different key predictors for each athlete: for Athlete 1, limb frequency was the strongest predictor; Athlete 2's performance depended mainly on a combination of overall limb frequency and maximum foot load; Athlete 3 exhibited a different technical style, marked by rapid foot transitions and a consistent hand movement rhythm. These results emphasize the need for personalized training strategies tailored to individual athlete characteristics in competitive speed climbing.

The study underscores the complex interdependence of biomechanical parameters in speed climbing, indicating that analyzing parameters in isolation may not provide a complete understanding of performance. Our findings highlight the importance of advanced analytical methods, such as the AI-based systems used in this research, to effectively capture the complex relationships between various performance metrics.

Despite the limitations of a small sample size and a cross-sectional design, this study demonstrates the promising potential of computer vision systems for detailed climbing performance analysis. The results suggest that incorporating both temporal and spatial parameters is essential for a comprehensive understanding of speed climbing techniques.

Future research should build on these findings using larger datasets, adopting longitudinal study designs, incorporating direct force measurement tools, using higher frame rate recordings, and including physiological metrics. Such comprehensive approaches would offer a more complete understanding of the factors influencing speed climbing performance and support the development of more effective coaching strategies and training programs in this fast-growing sport.

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