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Lateral End-Range Movement Profile and Shot Effectiveness During Grand Slam Tennis Match-Play

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ABSTRACT

End-range movements are among the most demanding but least understood in the sport of tennis. Using male Hawk-Eye data from match-play during the 2021–2023 Australian Open tournaments, we evaluated the speed, deceleration, acceleration, and shot quality characteristics of these types of movement in men's Grand Slam tennis. Lateral end-range movements that incorporated a change of direction (CoD) were identified for analysis using k-means (end-range) and random forest (CoD) machine learning models. Peak speed, average deceleration into the CoD, average reacceleration out of the CoD, and the quality of the shot played were computed. Players were grouped based on their ATP rankings (top 10, top 50, and outside top 50) to examine the influence of ranking on movement profiles and shot effectiveness. Our data showed that end-range movements profiles of top 10 and top 50 players were characterized by higher peak speed (d = 0.3–0.88), deceleration intensity (d = 0.25–0.63), and acceleration intensity (d = 0.06–0.51) when compared to players outside the top 50 ($p < 0.05$). Top 10 players also demonstrated greater peak speeds ($d = 0.59$) and acceleration intensities ($d = 0.45$) compared to top 50 players ($p < 0.05$). There was a nonlinear inverse relationship between peak speed and shot quality, such that, as peak speed increased, shot quality decreased—notwithstanding that top 10 players were more likely to hit high-quality shots at higher peak speeds. These results quantify the discrete kinematic characteristics of the sport's most challenging movement sequence and reveal, for the first time, that higher ranked players may possess superior movement potential on court.

1 | Introduction

The physical profile of professional tennis performance has largely focused on the accumulation of movement and displacement characteristics. Accordingly, we know that the cyclical movements between shots result in players covering 1500–2500 m per match (Pluim et al. 2023). However, these cumulative accounts of the movement demands of the sport mask the intermittent nature of tennis match-play (M. S. Kovacs 2006). Recently, more specific tennis movement analyses have emerged, with the cyclical movement between shots categorized into six distinguishable patterns, organizing what might otherwise represent an infinite number of possible movement scenarios (Armstrong et al. 2024a). Considered the most physically demanding of these movement patterns is the lateral end-range red (LERR) movement (Armstrong et al. 2024a). This movement pattern requires players to travel along or parallel to the baseline for, on average, 3.7 m pre-impact and 3.9 m postimpact (but up

Summary

- Top 10 ranked males are faster and accelerate harder during lateral end-range change of direction in match-play compared to those ranked > 10.
- Top 50 ranked males are able to decelerate harder during lateral end-range change of direction in match-play compared to those ranked > 50.
- Top 10 players hit *more* high-quality shots, when peak speeds are their highest.

to ~7.0 m pre- and/or postimpact) and with a time pressure value of 0.44 s (Armstrong et al. 2024a). A change of direction (CoD) also occurs in these movements around the time of ball impact, whether slightly before or during the CoD (Armstrong et al. 2024a). Importantly, the interaction between the distance requirements and time pressure of LERR movements results in high-speed movement. Furthermore, the CoD often occurs outside the singles sideline, which opens hitting angles for the opponent where reacceleration to reclaim the open court is key (Armstrong et al. 2024a; Carvalho et al. 2014). The LERR movement pattern is considered the most physically challenging in tennis, owing to the distance, time pressure, speed, and CoD attributes present when compared to other movement patterns identified (Armstrong et al. 2024a). However, very little is known about the kinematics present during this scenario, and therefore, more research is required to fully explore the demands of LERR movement in tennis match-play.

Assessing the speed, deceleration, and acceleration profile of LERR would provide coaches and athletes with a detailed understanding of the imposed demands during the most intense movements during match-play. This information may then be incorporated into training drills and physical profiling. For example, the magnitude of acceleration–deceleration expressed by the sport's best players near CoD during LERR could provide real-world benchmarks in commonly used assessments like the 5-0-5 CoD test (Armstrong et al. 2024a). The extent to which these peak speed requirements and deceleration/reacceleration characteristics within LERR vary across ranking/tennis ability is also unknown and may reveal further insights into the performance-determining nature of elite tennis movement.

The speed profile of players' LERR movements is of particular interest as higher entry speed into a shot can compromise hitting technique (Giles and Reid 2021). As inferred above, players will often use the width and depth of the court to open angles or create opportunities to attack, likely demanding LERR movements of opponents. This tactic is exploited commonly in baseline exchanges (Carvalho et al. 2014). In turn, higher proportions of defensive positioning punctuate the movement patterns of losing players during match-play (Martinez-Gallego et al. 2013). When these court positions are combined with LERR movement patterns, it is likely problematic for many players. Still, no work to date has examined the ability of tennis athletes to execute shots in highly demanding physical scenarios (such as LERR) during live matches, meaning that this remains speculative.

Accordingly, the aim of this study was to use men's Grand Slam match-play tracking data to describe the LERR movement pattern in terms of its peak speed, deceleration and acceleration characteristics in professional tennis competition while also considering the extent to which player ranking influences these kinematics. A secondary focus was to examine whether player ranking influenced shot outcomes during LERR movements. It was hypothesized that better ranked tennis players would possess superior movement characteristics and produce better shot outcomes when hitting at the end range.

2 | Materials and Methods

2.1 | Participants

Main draw male participants who competed during the 2021–2023 Australian Open campaigns were considered for this study. Each year, 128 males enter the tournament, which resulted in 169 unique athletes available for analysis. At the time of entry into the tournament, consent for data collection, analysis, and subsequent data reporting/publication was obtained from each athlete. An institutional human research ethics committee provided approval for the study (2022/ET000216).

2.2 | Data Collection

All main draw match-play movement data was captured via Hawk-Eye tracking technology (Hawk-Eye Innovations Ltd, Basingstoke, UK). This 10-camera system tracks ball and player coordinates during live match-play with acceptable precision and accuracy (Innovations 2015). Although player tracking accuracy is unpublished, similar precision to ball tracking is expected from previous results investigating human movement tracking with single camera systems (Dunn et al. 2014). Hawk-Eye staff provides raw sampled center of mass data with *X-Y* positional coordinates for each player during live match-play by collecting and processing video footages during the Australian Open, which is owned by the tournament. These data were then processed further to identify individual movement cycles where the LERR movement cycles were selected. This methodology is explained in detail elsewhere (Armstrong et al. 2024a, 2024b).

Once LERR movement patterns were identified, the movement cycles were then screened for CoD instances using a CoD detection model (Giles, Kovalchik, and Reid 2020). Briefly, this CoD detection model is a random forest algorithm which identifies medium and high-intensity CoD efforts using Hawk-Eye tracking data (*F*1-score = 0.729) (Giles, Kovalchik, and Reid 2020). If a CoD was not detected in the LERR movement cycle, this observation was removed. To isolate the movement of interest and subset each observation, peak speed was identified as the starting point in each movement cycle. The minimum speed around the CoD was identified, and the average deceleration between peak speed and minimum speed was calculated. Furthermore, average acceleration from minimum speed to peak speed post CoD was also computed. Outliers (identified using the IQR method) for any of the described variables resulted in the respective movement cycle being removed from the dataset. This resulted in 11,987 movement cycles utilized in this investigation.

Individual players were allocated into groups based on their ranking at the commencement of the tournament for each year. These groups included

1. Top 10 players (ranked 1–10)
2. Top 50 players (ranked 11–50)
3. Outside top 50 players (ranked > 50).

Player's data were considered on a yearly basis, and in the case that a player's ranking changed between years, each observation was allocated into the respective groups for that year. To evaluate a player's maximal expression of speed, deceleration, and acceleration during LERR movement cycles, the top three observations for each player each year were considered for analysis.

To evaluate shot effectiveness, a shot quality criterion was defined, and the shot played in each movement cycle was evaluated. All shots that resulted in a point being won (i.e., hitting a winner) were considered high quality, regardless of any shot-related characteristics. Previous work detailing the evaluation of shot quality explains high-quality shots land within close proximity (1-m) to the sideline or baseline (Kovalchik et al. 2020; Gillet et al. 2009), which highlights the importance of ball placement. Further consultation with elite tennis coaches and analysts revealed that ball speed is also a feature of shot quality. Accordingly, ball speeds in excess of the median speed for all groundstrokes (33.73 m/s) were considered to represent high-quality shots. At least one of these criteria was required for a shot to be considered high quality.

2.3 | Statistical Analysis

To understand the differences in maximal abilities expressed between groups during match-play, linear mixed models (LMM) were established for peak speed, average deceleration, and average acceleration. The linear mixed model is a form of robust linear model commonly used with similar sports data (Delaney et al. 2017) and was selected in this case for its ability to handle repeated observations of the same player between ranking groups on different years via inclusion as a random effect (Bates et al. 2015). Furthermore, for each model, the variable of interest (i.e., speed, deceleration, or acceleration) was the outcome variable and ranking group was a fixed effect. The assumptions of linearity, homoskedasticity, and normality of residuals were checked via the visual inspection of each model residual. To evaluate the difference between ranking groups, model estimates ± 95% confidence intervals (CI) were reported, alongside Cohen's effect sizes (d) and p-values with a significance set at $p \leq 0.05$.

The initial investigation of the relationship between shot quality and movement cycle peak speed revealed a nonlinear relationship, and therefore, a generalized additive model (GAM) was utilized to evaluate shot quality by peak speed. A GAM builds on the generalized linear model by accounting for flexible and nonlinear relationships between dependent and independent variables (Wood 2011). In this case, the binary outcome of shot quality was the outcome variable and player rank was the fixed effect. Peak speed was a smooth effect factored by rank and an interaction between player and year was a random smooth effect. An inverse logit function was used for all predicted values to account for the binary nature of the outcome variable and was expressed as a percentage likelihood of a successful outcome (i.e., chance of a high-quality shot). This accounted for the assumption of the linearity in the link function. The interaction between the player and year as a random effect also accounted for the assumption of independence of observations. All statistical computation was conducted using the R programming language (R version 4.1.3 [2022-03-10]), where LMM were fit using version 1.1–34 of the lme4 package (Bates et al. 2015) and GAM was fit using version 1.8–42 of the mgcv package (Wood 2011).

3 | Results

The LMM estimates are presented in Table 1 and comparisons between ranking groups are presented in Figure 1 (peak speed), Figure 2 (average deceleration), and Figure 3 (average reacceleration). Effect sizes between groups for each variable are presented in Table 2. There was a clear effect for player ranking on speed, deceleration, and acceleration, where better ranked players display faster speeds, harder decelerations, and higher reacceleration out of a CoD during LERR movement cycles (all $p < 0.05$).

Evaluation of shot quality resulted in significant smooth differences ($p < 0.01$), evident by the shape of the estimates presented in Figure 4. However, due to the relatively large standard error, model estimate results are likely similar across ranking groups for shot quality ($p > 0.23$). Generally, as the required movement cycle peak speed increased, shot quality decreased, with the optimal peak speed requirement located between 3.0 and 4.5 m/s. As a top 10 player, the best likelihood of hitting a high-quality shot during a high-intensity end-range scenario was 27.9%, which occurred when the peak speed was ~3.0 m/s. Players ranked 11–50 had the best chance of hitting high-quality shots (26.9% of the time) when required to move at a peak speed

TABLE 1 | Linear mixed model estimates ± 95% CI for peak speed, average deceleration, and average reacceleration per ranking group.

Ranking group	Observations (n)	Peak speed (m/s)	Avg. decel (m/s/s)	Avg. re-accel (m/s/s)
Top 10	26	5.92 ± 0.19	−9.04 ± 0.5	9.84 ± 0.6
Top 50	106	5.63 ± 0.09	−8.56 ± 0.24	9.15 ± 0.29
Outside top 50	217	5.48 ± 0.07	−8.24 ± 0.17	9.05 ± 0.21

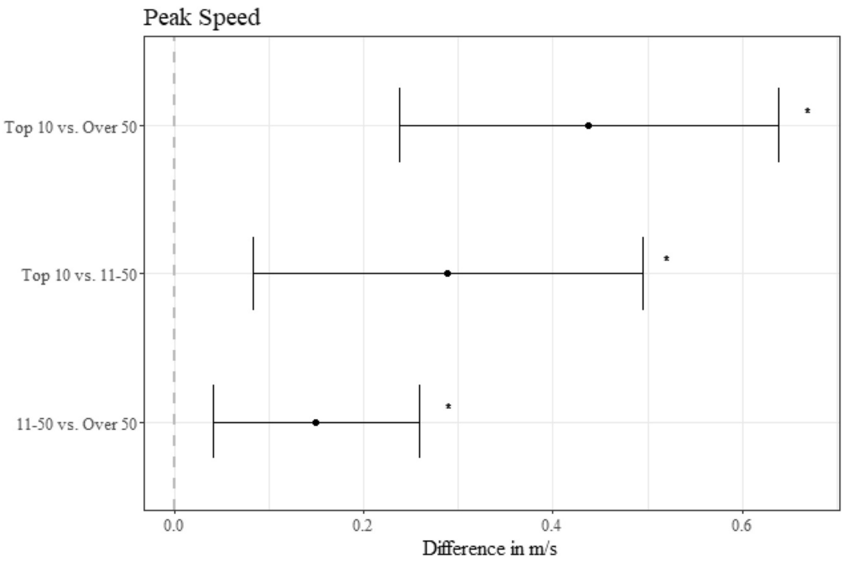

FIGURE 1 | Difference between ranking group model estimates (± 95% CI) for peak speed during lateral end-range red (LERR) movement patterns. $*p < 0.05$.

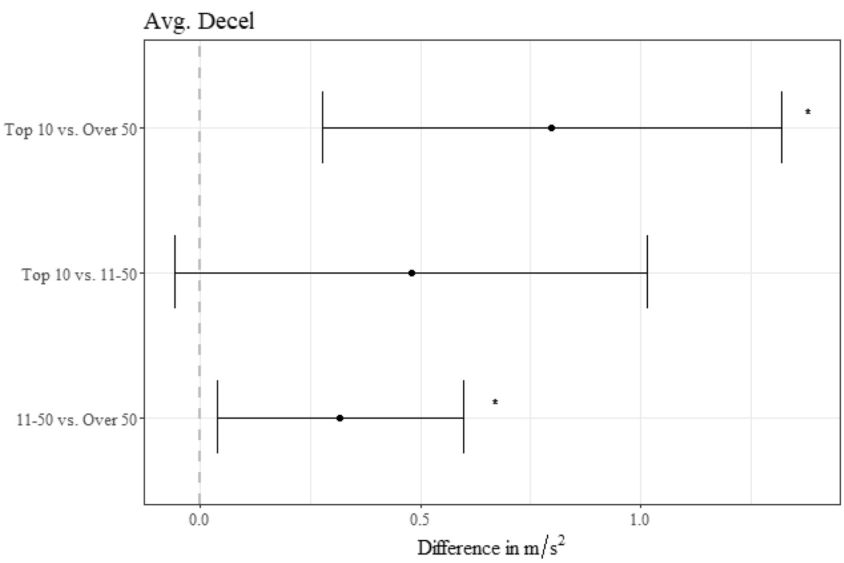

FIGURE 2 | Difference between ranking group model estimates (± 95% CI) for average deceleration during lateral end-range red (LERR) movement patterns. $*p < 0.05$.

of 4.2–4.3 m/s. Players ranked > 50 were 4%–5% less likely to hit high-quality shots in their optimal speed zone (22.7% at 4.2–4.4 m/s) compared to top 50 players.

4 | Discussion

This study investigated the speed, acceleration, and deceleration requirements during the most demanding spatiotemporal movement pattern in men's elite level tennis competition (i.e., the LERR with CoD). As hypothesized, better ranked players displayed different levels of physicality in the most challenging movement scenario in tennis match-play and hit high-quality shots more often at the top range of peak speed requirements than their lesser ranked counterparts.

Speed is an attribute that may distinguish movement ability in tennis (Giles et al. 2018). Indeed, our results suggest that better ranked players reach higher peak speeds in LERR movements. Maximal power production, reactive strength, and thigh angular velocity may be superior in better ranked players, which could explain the enhanced speed values observed in our results (Buchheit et al. 2014). Peak speed may also be influenced by deceleration ability, where poorer deceleration capability results in athletes self-regulating their peak speed in anticipation of stopping or changing directions (Harper et al. 2020, 2022). Therefore, the enhanced deceleration ability of better ranked players may help explain the observed differences in peak speed. Regarding deceleration and reacceleration, higher magnitudes of each were observed in better ranked players, highlighting their ability to brake and reclaim court positioning; which is reported as a critical ability in professional tennis (Carvalho

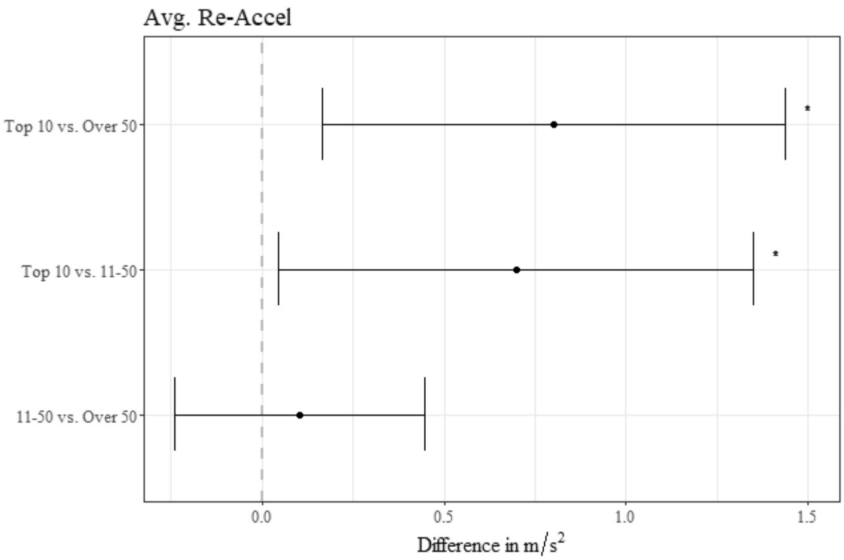

FIGURE 3 | Difference between ranking group model estimates (± 95% CI) for average reacceleration during lateral end-range red (LERR) movement patterns. *$p < 0.05$.

TABLE 2 | Cohen's *d* effect sizes and *p*-values for peak speed, average deceleration, and average reacceleration between ranking group.

Comparison	Effect size (*d*)	Interpretation	*p*-value
Speed			
Top 10 vs. top 50	0.59	Medium	< 0.05
Top 10 vs. outside top 50	0.88	Large	< 0.05
Top 50 vs. outside top 50	0.30	Small	< 0.05
Deceleration			
Top 10 vs. top 50	0.38	Small	0.08
Top 10 vs. outside top 50	0.63	Medium	< 0.05
Top 50 vs. outside top 50	0.25	Small	< 0.05
Acceleration			
Top 10 vs. top 50	0.45	Small	< 0.05
Top 10 vs. outside top 50	0.51	Medium	< 0.05
Top 50 vs. outside top 50	0.06	Trivial	0.50

et al. 2014). An important facet worthy of mention, tennis is a unique sport where sliding during deceleration and CoD is a prominent technique employed. The ability of a player to slide during the CoD will impact deceleration and can change the biomechanical requirements during a CoD event (Ferrauti et al. 2013). It could be surmised that better ranked athletes possess superior physical qualities (e.g., higher maximal power output or reactive strength), allowing higher magnitudes of speed, deceleration, and acceleration in match-play (Harper et al. 2020, 2022; Harper, Jordan, and Kiely 2021). However, another explanation may be that better ranked players utilize more efficient footwork strategies during CoD events (i.e., sliding), which improve deceleration without necessitating superior physical capability (Harper et al. 2022), although further research is needed to elucidate such outcomes.

Tennis consists of high acceleration and deceleration demands (M. S. Kovacs 2006; Giles, Peeling, and Reid 2021; M. S. Kovacs, Roetert, and Ellenbecker 2008), and yet, current research is constrained to the number of efforts at the elite level. Our results show that tennis athletes record average deceleration intensities of ~9.0 m/s^2 and acceleration intensities of ~9.9 m/s^2 during CoD tasks. Of the limited comparable data available in the literature, elite soccer players have been shown to produce average deceleration intensities of 4.99 m/s^2 in testing-based environments (Harper et al. 2020), with a theoretical maximal acceleration of ~7.7 m/s^2 (Morin et al. 2021). This highlights the physicality of professional tennis and underlines why CoD performance is a large focus of tennis training and conditioning programs (Giles, Peeling, and Reid 2021; Galé-Ansodi, Castellano, and Usabiaga 2017). Furthermore, within the tennis cohort, the highest intensity of average deceleration during LERR movement cycles is distinguishable between top 50 players and those ranked > 50. Our results show similar average deceleration values between top 10 and top 50 players; however, the reacceleration of top 10 players was distinguishable from top 50 players and those ranked > 50. Such outcomes provide data-driven physical benchmarks for coaches working with players across different rankings.

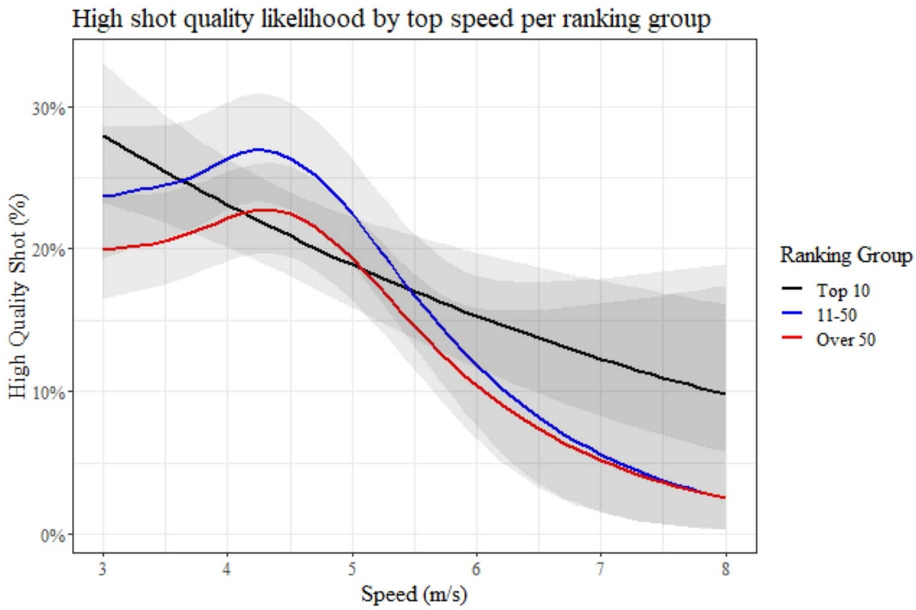

FIGURE 4 | Generalised additive model (GAM) estimates (± 95% CI) for high-quality shot likelihood as a function of required peak speed during lateral end-range red (LERR) movement patterns between ranking groups.

Our findings suggest the physical abilities of tennis professionals are associated with their ranking, and as such, improving the physical performance of players may elevate their game and facilitate improved ranking. However, the physical qualities that determine tennis performance are complex, where several performance measures (e.g., ground contact time, countermovement jump height, and 7-m sprint time) have been shown to poorly correlate with tennis-specific movements (Ferrauti et al. 2013). A lack of tennis-specific movement assessments has been offered as justification for the poor correlation, and therefore the methodology for evaluating LERR movement detailed in the current investigation may help to fill this gap in an ecologically representative way. The current approach to measure deceleration (i.e., average deceleration from peak speed to minimum speed) has been explored in other sports (i.e., soccer) where reports of strong relationships between several variables measured from the countermovement jump (CMJ) are observed (Harper et al. 2020). Specifically, concentric forces (both peak and mean) and mean power measured from CMJ tests were higher in those with better average deceleration values (Harper et al. 2020). Furthermore, higher concentric strength of both the knee flexors and extensors is considered a critical factor during deceleration performance (Harper, Jordan, and Kiely 2021). As such, research is warranted to understand how these physical qualities manifest in tennis athletes specifically and their impact on deceleration performance during LERR movement patterns.

The results from our GAM smooth splines show a unique pattern for the top 10 players of declining shot quality as peak speed demands increase. Additionally, the top 10 player shot quality was also higher (~15%) than players ranked > 10 when speed requirements are > 5.5 m/s. Players ranked outside the top 10 (i.e., top 50 and > 50) share a similar smooth spline shape, with the top 50 players having a slightly higher likelihood of hitting high-quality shots compared to those ranked > 50. This suggests that the best players in the world can produce high-quality shots more often, particularly when the peak speed required to reach the ball is at its highest. Considering LERR movements present during ~13% of all movement cycles in Grand Slam tennis (Armstrong et al. 2024a), higher quality shot output in this scenario may be the difference between winning and losing a match. Of note, it may be that the top 10 players have a greater potential top speed based on the results of the peak speed model, and therefore, are operating at a lower percentage of their true maximum sprint speed during these high-speed movements in match-play. Such prospects would give these players more control under LERR circumstances. However, it is unclear as to how close tennis athletes are to reaching their maximum sprint speed in match-play and future research comparing the peak physical ability from testing (i.e., maximal sprint speed from a sprint test) to the expression of speed during competitive matches would be useful. Additionally, evaluating the effectiveness of a physical training program which targets peak speed, acceleration, and deceleration ability against an athlete's LERR physical profile would provide insights into how trainable these attributes are in benefitting match-play scenarios.

5 | Practical Applications

Clearly, the physical profile of tennis athletes is important to successful performance (M. S. Kovacs 2006; M. Kovacs 2007; M. S. Kovacs 2007). Our results support the notion that physically superior athletes are better ranked and can execute high-quality shots under extreme physical circumstances compared to their lower ranked counterparts. Accordingly, training the peak speed, deceleration, and reacceleration abilities of tennis athletes are likely important to enhancing tennis performance. This contention is supported by research showing that training an athlete's maximal concentric power and reactive strength can facilitate the development of maximal speed and acceleration, ultimately enhancing tennis match-play performance (Buchheit et al. 2014). Furthermore, improving the concentric force and power of the leg extensors and flexors can improve the deceleration ability of tennis athletes and improve their performance on-court (Harper et al. 2020, 2022).

6 | Limitations

The results of this investigation are constrained to professional males on hard court surfaces. Therefore, the results should be interpreted with caution in relation to females, juniors, or other court surfaces. Furthermore, the peak speed, average deceleration, and average reacceleration figures presented in this study are the results of a markerless motion capture technology and generalizing these values to those produced by other technologies measuring physical performance (i.e., global positioning systems [GPS] and linear position transducers) is difficult. Practitioners should understand the differences in results that might emanate from different technologies. As such, future research comparing the agreement between tracking technologies in tennis (e.g., GPS vs. Hawk-Eye) is warranted. Similarly, more empirical work is needed to compare the physical attributes present in the LERR movement profile across surfaces or between tennis demographics.

7 | Conclusion

This study provides insights into the kinematic demands of high spatiotemporal movement patterns in elite male Grand Slam tennis match-play. We revealed that players ranked in the top 10 express greater speed, and during CoD tasks, greater reacceleration intensity than those ranked > 10 and > 50 in the world. Those players in the top 10 and top 50 have similar deceleration abilities but are superior to those ranked > 50. Further, the top 10 players are also able to execute high-quality shots when peak movement speeds are at their fastest, which manifests as an inverse exponential relationship between speed and shot quality. Finally, players ranked > 10 in the world appear to have a different relationship with speed and shot quality. The results of this study may serve as a benchmarking guide for practitioners and athletes as to how the best tennis athletes in the world move and execute shots in the most demanding movement scenario in tennis match-play. Furthermore, this investigation provides reference data to trainable attributes that can enhance on-court tennis performance and should be considered pivotal in the development of a competitive professional athlete.

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Ethics Statement

The University of Western Australia research ethics committee provided the ethical approval for the study (2022/ET000216).

Consent

Consent for data collection and analysis for this study was obtained prior to each tournament at the time of entry.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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