Full Title: Determining stroke and movement profiles in competitive tennis match-play from wearable sensor accelerometry

Abstract

This study determined stroke and movement accelerometry metrics from a wearable sensor and compared between court surface (grass vs. hard) and match outcome (win vs. loss) during competitive tennis match-play. Eight junior high-performance tennis players wore a trunk-mounted GPS, with in-built accelerometer, magnetometer and gyroscope during singles matches on hard and grass courts. Manufacturer software calculated accelerometer-derived total Player Load (tPL). A prototype algorithm classified forehands, backhands, serves and “other” strokes, thereby calculating stroke player load (sPL) from individual strokes. Movement player load (mPL) was calculated as the difference between tPL and sPL, with all metrics reported as absolute and relative ($\cdot min^{-1}$, %, $\cdot$stroke). Analysis of accelerometer load and stroke count metrics were performed via a two-way (surface [grass vs. hard] x match outcome [win vs. loss]) ANOVA ($p < 0.05$) and effect sizes (Cohen’s *d*). No interaction effects for surface and match outcome existed for absolute tPL, mPL and sPL (p>0.05). Increased mPL% featured on grass courts, while sPL% was increased on hard courts (p=0.04, d=1.18[0.31-2.02]). Elevated sPL$\cdot$min^{-1} existed on hard courts (p=0.04, d=1.19[0.32-2.04]), but no differences in tPL$\cdot$min^{-1} and mPL$\cdot$min^{-1} were evident for surface or outcome (p>0.05). Relative forehand sPL (FH-sPL$\cdot$min^{-1}) was higher on hard courts (p=0.03, d=1.18[0.31-2.02]) alongside higher forehand counts (p=0.01, d=1.29[0.40-2.14]). Hitting demands are heightened on hard courts from increased sPL and counts. Conversely, increased mPL% on grass courts likely reflect the specific movement demands from point-play. Physical preparation strategies during training blocks can be tailored towards movement or hitting loads to suit competitive surfaces.

Key Words: athlete monitoring, external workload, physical demands

INTRODUCTION

Understanding the stroke and movement activities of tennis players during competition can inform the design of conditioning and skills training to enhance athlete preparation (28). Contemporary methods for understanding these competitive loads in other sports exist through wearable technologies (i.e., global positioning systems [GPS] and accelerometry) (20); however, the uptake of this technology in tennis has been slow. This is likely the result of restrictive regulations from governing bodies, as well as the sport's complex activity profile. Indeed, the physical demands of tennis involve acyclic, high-speed actions of the upper and lower limbs to execute stroke and movement demands (27), though current wearable metrics seemingly represent lower-body activity (20). Previous uses of wearable technology in tennis have quantified whole-body match-play movement via GPS measures, such as distance covered, metres per minute, etc. (7), largely failing to distinguish between lower (traversing the court) and upper (hitting the ball) body actions. Thus, implementation and understanding of microtechnology to determine concurrent movement and hitting load within match-specific contexts (i.e., court surface, match outcome) is important for the future of physical preparation and monitoring in tennis.

Accelerometry-derived measures of workload during match-play vary based on manufacturer-specific processing systems (i.e., "Player Load™"), though report the sum of accelerations from running, jumping/landing and rotations in arbitrary units (AU) (3). The vagaries observed in tennis accelerometer load data are noted, where absolute values >3900 AU were reported in players aged 13-15y during simulated clay-court competition (25); whilst another study on clay reported 395-418 AU from longer match durations with similar aged athletes (12). Such discrepancy could be due to different accelerometer data processing methods between studies given matches in the latter study were longer (81.2 min vs. 61.7 min) with greater distance covered. Hence, how these findings inform training prescription and match planning remain to be determined. Separately, movement intensity has also been inferred from accelerometer data to reveal an effect for court surface, with clay court matches eliciting more frequent movement events at greater acceleration magnitudes compared to hard courts (24). Additionally, tennis movement profiles may also be influenced by match outcomes, as players who win points were reported to cover an additional four metres per point (19). However, these alterations in movement demands due to surface or match outcome exist as a requirement of stroke execution during point-play. Accordingly, wearable devices that can report concurrent but separate physical and hitting demands remains a gap in current literature.

Whilst tennis movement volume and intensity are reported from accelerometer units, stroke loads are typically limited to volume-based measures from video coding (15). Such observations have revealed typical stroke demands on hard courts to consist of 5.9 ±0.1 strokes/rally (30) and result in cumulative volumes of 274 ± 174 strokes/match (26). Similar to movement profiles, court surface influences hitting volumes due to altered rally length; which, on fast surfaces such as hard and grass courts, result in decreased stroke counts per rally and reductions in cumulative point-play time (4, 29). Accordingly, this could be postulated to mitigate upper limb loading profiles relative to movement, which possibly alters training foci during tournament preparation. However, determining this remains speculative and requires concurrent measures of stroke and movement demands. Such concepts have been introduced to a degree in other racket sports, such as badminton, and suggests accelerometry profiles measured at the upper and lower limbs are influenced by stroke type (17). Consequently, this points to possibilities in tennis for reporting respective movement and hitting demands from a single wearable sensor during match-play. Thus, the aims of this study were: 1) to describe the accelerometer loads for stroke and movement actions (from a single sensor) in junior-elite tennis match-play, 2) to compare the accelerometer stroke and movement loads between hard and grass courts, and 3) to compare accelerometer stroke and movement load between winners and losers.

METHODS

Experimental Approach to the Problem

A cross-sectional observational study design was employed to capture respective movement and hitting accelerometer loads obtained from a wearable sensor during hard and grass court tournament blocks in a group of junior-elite male tennis players. A prototype algorithm, developed from the wearable sensor's accelerometer, gyroscope and magnetometer outputs, was used to classify tennis stroke events with >90% accuracy and consequently determined stroke-specific player load (i.e., sPL). Movement demands (i.e., mPL) were inferred from the difference between traditional player load and the sPL metric. Match result was recorded for each player to examine the effect of winning and losing on respective sPL and mPL metrics.

Subjects

Eight junior-elite male tennis players (age 15.5 ± 1.6 y) were recruited for this study. The players were part of Tennis Australia's National Academy program in both Adelaide and Sydney. As per Tennis Australia's youth development guidelines, players engaged in: 1) ≈20 h of on-court training per week, 2) ≈6 h off-court training per week and 3) were competing in regular International Tennis Federation (ITF) sanctioned junior tournaments. All players were right-handed and utilised and a double-handed backhand. The university's Human Research Ethics Committee (HREC) approved this study (ETH19-4062). Parental consent was obtained for players' participation in the study.

Procedures

Data was collected across three separate tournaments in Australia, including the Adelaide ITF Grade 5, Australian Grass Court Nationals and Australian Hard Court Nationals, occurring in September, October and December 2019, respectively. Plexicushion hard courts were used in both the Adelaide ITF and hard court events, with natural grass used in the grass event. Singles matches were contested as a best-of-three sets and were legislated in accordance with the rules of the ITF (13). Twenty-nine singles match observations were captured for analysis accounting for 4 ± 3 match observations per player (outlined in Table 1 and Table 2). Of note, two players from the sample contested both hard and grass court tournaments.

All players wore a global positioning systems (GPS) unit (Catapult OptimEye S5, Catapult Sports, Melbourne) between the scapulae and housed in the manufacturer-designed harnesses, which allowed for minimal movement on the skin (21). The GPS unit sampled at 10 Hz with an in-built triaxial accelerometer sampling at 100 Hz, though for the purposes of this study, only the accelerometer data was analysed. PlayerLoad™ (i.e., player load, PL) was the predominant measure in this study and is defined as the square root of the sum of instantaneous accelerations in the medio-lateral (x), vertical (z) and antero-posterior (y) planes and is presented in arbitrary units (AU). Reliability of the PL metric has previously been established at 1.9% coefficient of variation (CV) from observations in team-sport athletes (2). Further, all matches were video recorded using Sony video cameras (HDR-CX700VE, Sony, Japan) and positioned 10 m and 6 m behind the baseline in accordance with previous match protocols (23, 26).

Raw accelerometer data was downloaded and processed via the manufacturer's custom software (OpenField 2.3.4, Catapult Sports, Melbourne), with PL determined via custom-developed prototype algorithms; though, it is noted that varied methods of calculation have been reported (3). This process enabled the calculation of a traditional generic PL, herein defined as total player load (tPL), as previously described (1). In addition, the raw accelerometer data was exported and stored as a comma-separated values (.csv) file to be further analysed to discern the PL specific to stroke actions. Investigations from Catapult Sports (Catapult Sports, Melbourne) on a prototype algorithm documented in an internal "white paper" describes the machine learning models implemented to detect 'forehand drive' (FH), 'backhand drive' (BH), 'serve' and 'other stroke' (other) events based on absolute rotation yaw values and showed respective accuracies of 94%, 96.5%, 99.9% and 83.5% (Personal Communication, Catapult Sports). The "other" stroke category from the prototype algorithm may encompass volley or "end-range" strokes that are not captured within respective FH or BH "drive" categorisations. We have recently tested these findings, with our unpublished work revealing respective accuracies of 89%, 94% and 98% for 'forehand', 'backhand' and 'serve' swings from comparing manually coded stroke events to the stroke event detection from the prototype algorithm. Following stroke detection and classification, the prototype algorithm is trained over a one-second window (i.e., 0.5 s before and after event detection) to quantify the sum of accelerations (i.e., PL) and is classified in the present study as stroke-specific PL (sPL). Hence, determination of sPL allowed for separation of movement-based PL (mPL) by subtracting sPL from tPL determined from the manufacturer software.

The processed file from Catapult Sports contained the coordinated universal time (UTC) of each stroke event, which was used in combination with the video footage to time align the start and end times of each set and match on the manufacturer software. This ensured the data captured are reflective of those experienced throughout each set and excludes the between-set changeover activity. Accordingly, all player movement and stroke activities captured during set-times were included for analysis. Using this dataset, stroke counts and respective PL metrics across the four categories were quantified for each match and reported as sPL derivatives (i.e., FH-sPL). All load metrics were reported in both absolute (AU) and relative (per minute [$AU \cdot min^{-1}$]) metrics across matches, with sPL and mPL also reported as a proportion (%) of tPL to account for match duration. Stroke count data was reported in both absolute (n) and relative ($n \cdot min^{-1}$) terms across the four respective stroke categories. Additionally, the sPL associated with respective strokes was classified in absolute and relative terms as described previously, though an additional relative metric of $AU \cdot stroke$ was reported for respective stroke type.

Statistical Analyses

All statistical analysis was performed in the R language (RStudio, 1.1.463, RStudio, Inc.). Descriptive statistics of the mean and standard deviation were used across all player load and stroke count variables in all matches. Normality of data was first assessed via Shapiro-Wilk's test, with non-normally distributed log-transformed. To investigate the effect of surface and match outcome on all accelerometer load metrics and stroke count data, a two-way (surface x match outcome) analysis of variance (ANOVA) with Tukey's post-hoc test was performed. Due to the large number of variables in the present study, Bonferroni's correction was applied to minimise the risk of Type II errors. Significance level was set at 0.05. Effect size (ES) was calculated using Cohen's d statistic with d<0.2 classified as trivial, d=0.2-0.5 small, d=0.5-0.8 medium, and d>0.8 large, with 95% confidence intervals (CI).

RESULTS

Table 1 presents accelerometer metrics across all hard and grass court matches for winning and losing outcomes. There were no significant interaction effects observed for absolute or relative tPL (p=0.78 and p=0.80, respectively) or absolute and relative mPL (p=0.67 and p=0.58, respectively). Further, no significant interaction effects were observed for the proportion of mPL (mPL%) (p=0.18); however, a significant main effect for court surface existed, showing greater mPL% on grass than hard courts (p=0.04, d=1.18[0.31-2.02]). Absolute and relative sPL showed no significant interaction effects for surface and match outcome (p=0.80 and p=0.25, respectively), though significant main effects for court surface demonstrated a decreased sPL on grass courts (p=0.04, d=1.19[0.32-2.04]). No significant interaction effects existed for sPL proportion (sPL%) (p=0.18), though a significant main effect for court surface showed increased sPL% on hard courts (p=0.04, d=1.18[0.31-2.02]). No significant main effects for match outcome were observed for any absolute or relative tPL, sPL or mPL metric (p>0.05).

Absolute and relative sPL specific to the four stroke categories (i.e., forehand, backhand, serve and other) are also presented in Table 1. Across respective stroke types, there were no interaction effects for absolute or relative sPL (p>0.05). However, a main effect for court surface was observed for FH-sPL·min^{-1} (p=0.03, d=1.18[0.31-2.02]). No significant differences existed for main effects of court surface or match outcome for sPL, sPL·min^{-1} or sPL·stroke within any respective stroke category (p>0.05).

*****TABLE 1 NEAR HERE*****

Table 2 shows stroke count metrics for all matches and categorised by court surface and match outcome. No significant interaction effects were observed across all absolute stroke counts (p>0.05). There were no significant main effects for court surface or match outcome for absolute stroke counts (p>0.05, d=0.23-0.77[-0.50-1.56]). No significant interaction effects existed for relative stroke counts (p>0.05); however, a significant main effect for court surface was observed for FH·min^{-1} and showed greater values on hard compared to grass surfaces (p=0.01, d=1.29[0.40-2.14]). Conversely, BH·min^{-1} showed no main effect for court surface (p=0.12, d=1.02[0.17-1.84]). No main effects existed for relative serve and other stroke counts (p>0.05, d=0.00-0.50[-0.76-1.28]). No significant differences in stroke count metrics were evident based on match outcome (p>0.05). Stroke-specific sPL is reported within the respective stroke categories in Table 2. No significant interaction effects existed for all stroke types (p>0.05). No significant main effects for court surface or match outcome existed for sPL·stroke across remaining BH, serve or other stroke categories (p>0.05).

*****TABLE 2 NEAR HERE*****

DISCUSSION

This study reports a novel approach to accelerometry measures in tennis via describing concurrent movement and stroke match-play demands from a single wearable sensor and comparing the effect of court surface and match outcome. Whilst no significant differences existed for tPL based on surface or outcome, reduced mPL% on grass courts and increased sPL% on hard courts points to differential lower limb (locomotion) and upper limb (hitting) demands on the two surfaces. This finding is further supported by greater sPL·min^{-1} evident on hard courts, likely due to higher FH·min^{-1} and resultant FH-sPL·min^{-1}, which suggests tactical approaches influence hitting demands and in turn upper/lower limb load. Accordingly, coaching and sport science staff in tennis can start to quantify these novel measures of PL to interpret hitting and moving demands during match-play and subsequently guide future athlete preparation strategies.

Accelerometer-based measures are useful for court sports given the acceleration and deceleration actions occurring in confined spaces (10) and thus, are suited to investigations of tennis-specific demands. We observed tPL values of 548 ±235 AU and 507 ±92 AU on respective hard and grass court matches, which are higher than previous observations in younger populations (12) and more reflective of observations in adult males (8). Similar tPL or tPL$\cdot$min^{-1} characterised match-play regardless of match outcome, which is consistent with previous work (12). Additionally, court surface did not affect tPL, which may be an artefact of the surfaces generally attracting similar court pace ratings (4), producing lower and faster ball bounces, shorter rally lengths and less active playing time (29). This finding adds to previous knowledge of tPL in tennis, whereby increased accelerometer loads have been observed on slow versus fast (i.e., clay vs. hard) surfaces (24) as a product of increased movement demands and longer point durations. It is also plausible that more subtle surface or outcome effects may have been masked by the variation in the playing styles of the small cohort (5), which would have been partly mitigated had the match-ups been controlled or a larger sample obtained. Accordingly, it is recognised that individual playing style from the opponent will influence match activity profiles and resultant accelerometer load, though this could not be controlled during official tournament settings.

The measurement of hitting demands through sPL, alongside measures of court movement (mPL), is a novel aspect of this study. The revelation that sPL% was greater on hard courts compared to grass courts points to heightened relative hitting-induced accelerometer loads. Previous tennis research reports shorter point lengths and cumulative time spent in point-play on grass courts, leading to reductions in relative stroke-play volume (4) and may explain the observed reduction of sPL% on grass. As hard and grass courts are grouped as “fast” surfaces (29), the sensitivity of sPL measures to detect increases on hard courts may hint at future applications of accelerometry in tennis to distinguish playing demands historically masked by oversimplified classifications of court speed. Whilst speculative, the increased FH·min^{-1} and FH-sPL·min^{-1} observed on hard courts may be a reflection of the increasingly forehand-dominant approach of junior tennis matches, which contribute ≈44% of strokes during hard court match-play (16). Conversely, successful grass court match strategies include utilising the slice stroke (11), which is currently not a classification in the prototype algorithm and differences in hitting activity with this stroke across court surface remains unclear.

Movement strategies are often altered by players based on court surface, where the friction and rebound coefficient of these surfaces require different temporal and coordinative demands (6). Interestingly though, our current mPL or mPL·min^{-1} measures were similar between hard and grass courts, which could be explained by a number of factors. First, it may be that enough of the sport's gross locomotion demands are similar between these two court surfaces, as has been suggested on hard and clay courts (18) that subtle contextual load differences (such as anticipatory changes in direction or initiation of movement) are muted and gross accelerometry measures are comparable. Second, it is plausible that players adapt their deceleration strategies to preserve stroke integrity regardless of the frictional characteristics of court surface (9) and that current mPL metrics, as a difference between tPL and sPL, are not sensitive enough to detect any mechanical variation. Alternatively, as has been widely reported elsewhere (4), players may simply spend less time in point-play on grass and movement load may reflect locomotion during change-overs and between points.

Match activity and movement profiles contextualised by winning or losing may influence conditioning practices, especially for continuation through tournament rounds. However, the present study observed little evidence of a difference in mPL metrics based on match outcome.

This agrees with the work of Kilit and Arslan (14), who reported trivial differences in the average acceleration (measured via *g* force) of winning and losing players in junior tennis, but contrasts with reports in professional men's tennis that winning players cover an additional 2-4 metres per point (19, 28). While this may reflect actual differences in tennis match-play amongst professional players with greater physical development, it is possible that measurement differences also explain the similarity in mPL for winning and losing. Accordingly, future accelerometry research conducted in tennis at the point-level may lead to improved standardisation of methodologies and measurement of movement profiles to better differentiate these contexts.

The prototype algorithm used in the present study is acknowledged as presenting possible limitations. Indeed, stroke classifications are limited to being more generic in nature, with future developments required to capture more explicit stroke type descriptions. Further it is unclear when the specific event detection for stroke classifications occurs, which may impact the contribution of pre- and post-stroke activity reflected in sPL metrics. This study is also limited by its small sample size; however, this is an unavoidable result of the limited scholarship athletes within high-performance tennis academies. Accordingly, we acknowledge the limitation in generalising our findings to broader tennis populations and suggest practitioners consider the application of mPL and sPL metrics for more refined on-court exposure measures. A further sample-related limitation is the absence of female data, which may present an area for future research given observed sex effects in the movement demands of elite players (31). Additionally, the set-level analyses implemented in the present study may mask subtle differences in respective stroke and movement demands at more granular levels of tennis (i.e., point, game) (27) and thus, reflects a potential area for future research. Lastly, investigating the influence of match outcome in junior tennis players represents a possible limitation due to unrefined game-styles that result from varying technical, tactical, and physical skills.

This study quantified accelerometer load in tennis match-play through concurrent reporting of stroke and movement load metrics and compared these measures across court surface and match outcome. The key results of this study were sPL metrics are impacted by court surface but not match outcome. Indeed, hard court matches elicit greater stroke load and counts relative to grass courts, with particular manifestation in heightened hitting demands on the forehand side. Limited differences in mPL metrics likely reflect adaptations to movement strategies across surface to uphold stroke execution. Accordingly, the results of the present study show promise for use of a single wearable sensor to determine concurrent hitting and movement demands in tennis to then guide athlete training and tournament preparation.

PRACTICAL APPLICATIONS

Strength and conditioning staff working in tennis can maximise available training block time in targeting movement- or stroke-specific physical adaptations dependant on the competitive surface. Within grass court tournament blocks, detraining effects due to match-play exposures (22) may be heightened due to lower time spent in point-play (i.e., reduced $sPL \cdot min^{-1}$) and could require supplementary drills from conditioning staff to mitigate this occurrence. For sport science practitioners, load monitoring surveillance via accelerometry measures can be confidently implemented during training blocks given the sensitivity of sPL to court surface changes, which is reflective of different stroke types used and overall hitting volumes. Lastly, technical coaches can utilise stroke count measures to improve understandings of hitting load exposures across stroke type during competitive periods.

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Table 1. Mean ±standard deviation of accelerometer load metrics in singles matches across hard and grass courts amongst winning and losing players

Load Variable	Hard Court Matches (n = 19)	Grass Court Matches (n = 10)	Hard Court Winners (n = 9)	Hard Court Losers (n = 10)	Grass Court Winners (n = 6)	Grass Court Losers (n = 4)
Player Load (AU)	548 ±235	507 ±92	490 ±250	599 ±221	457 ±86	583 ±25
Movement Player Load (AU) (Proportion of Player Load [%])	431 ±185 (79 ±5)$^{*(4)}$	419 ±72 (83 ±2)	380 ±192 (77 ±6)	478 ±176 (80 ±2)	382 ±69 (84 ±1)	475 ±18 (82 ±1)
Stroke Player Load (AU) (Proportion of Player Load [%])	116 ±55 (21 ±5)$^{*(4)}$	88 ±22 (17 ±2)	110 ±64 (23 ±1)	121 ±48 (20 ±2)	75 ±17 (16 ±1)	108 ±10 (18 ±1)
Player Load (AU·min^{-1})	6.07 ±0.51	5.55 ±0.25	6.20 ±0.59	5.95 ±0.41	5.57 ±0.17	5.53 ±0.38
Movement Player Load (AU·min^{-1})	4.76 ±0.37	4.59 ±0.23	4.78 ±0.42	4.73 ±0.34	4.65 ±0.14	4.51 ±0.34
Stroke Player Load (AU·min^{-1})	1.31 ±0.37$^{*(4)}$	0.96 ±0.09	1.42 ±0.49	1.21 ±0.18	0.92 ±0.08	1.02 ±0.08
Forehand Player Load (AU)	40 ±28	24 ±12	42 ±34	39 ±23	18 ±9	32 ±10
Backhand Player Load (AU)	36 ±18	25 ±8	32 ±21	40 ±16	22 ±10	29 ±4
Serve Player Load (AU)	30 ±9	28 ±6	28 ±8	32 ±10	25 ±7	32 ±2
Other Stroke Player Load (AU)	9 ±4	12 ±4	9 ±4	10 ±5	11 ±3	15 ±4
Forehand Player Load (AU·min^{-1})	0.44 ±0.20$^{*(4)}$	0.25 ±0.10	0.52 ±0.25	0.37 ±0.11	0.22 ±0.11	0.30 ±0.08
Backhand Player Load (AU·min^{-1})	0.41 ±0.16	0.27 ±0.06	0.41 ±0.21	0.41 ±0.13	0.26 ±0.06	0.28 ±0.06
Serve Player Load (AU·min^{-1})	0.35 ±0.08	0.31 ±0.06	0.38 ±0.09	0.33 ±0.07	0.31 ±0.07	0.30 ±0.04
Other Stroke Player Load (AU·min^{-1})	0.10 ±0.03	0.13 ±0.03	0.12 ±0.04	0.10 ±0.02	0.13 ±0.03	0.14 ±0.04

All data presented as mean ±standard deviation.
*significant main effect for surface (p<0.05).
$^{(4)}$large effect size (d>0.8).

Table 2. Mean ±standard deviation of stroke count and individual stroke load metrics in singles matches across hard and grass courts amongst winning and losing players

Load Variable	Hard Court Matches (n = 19)	Grass Court Matches (n = 10)	Hard Court Winners (n = 9)	Hard Court Losers (n = 10)	Grass Court Winners (n = 6)	Grass Court Losers (n = 4)
Forehand Count (n)	166 ±90	113 ±54	168 ±101	165 ±84	86 ±40	153 ±50
Backhand Count (n)	122 ±52	93 ±32	104 ±57	138 ±42	87 ±38	102 ±20
Serve Count (n)	97 ±28	99 ±22	84 ±18	107 ±32	88 ±21	116 ±3
Other Stroke Count (n)	49 ±23	67 ±17	44 ±17	54 ±28	59 ±10	78 ±21
Forehand Count ($n \cdot min^{-1}$)	1.86 ±0.64*(4)	1.20 ±0.47	2.14 ±0.73	1.60 ±0.43	1.05 ±0.47	1.42 ±0.41
Backhand Count ($n \cdot min^{-1}$)	1.39 ±0.47	1.01 ±0.27	1.34 ±0.56	1.44 ±0.40	1.03 ±0.29	0.98 ±0.30
Serve Count ($n \cdot min^{-1}$)	1.13 ±0.24	1.09 ±0.15	1.16 ±0.26	1.10 ±0.23	1.07 ±0.18	1.10 ±0.10
Other Stroke Count ($n \cdot min^{-1}$)	0.56 ±0.17	0.65 ±0.17	0.59 ±0.22	0.52 ±0.11	0.73 ±0.13	0.74 ±0.18
Forehand Player Load (AU/stroke)	0.23 ±0.03	0.21 ±0.01	0.23 ±0.04	0.23 ±0.03	0.20 ±0.01	0.21 ±0.01
Backhand Player Load (AU/stroke)	0.29 ±0.04	0.27 ±0.05	0.30 ±0.04	0.29 ±0.05	0.26 ±0.04	0.29 ±0.05
Serve Player Load (AU/stroke)	0.32 ±0.04	0.28 ±0.02	0.33 ±0.04	0.30 ±0.04	0.29 ±0.02	0.27 ±0.02
Other Stroke Player Load (AU/stroke)	0.19 ±0.01	0.18 ±0.01	0.20 ±0.02	0.18 ±0.02	0.18 ±0.02	0.19 ±0.00

All data presented as mean ±standard deviation.
*significant main effect for surface (p<0.05).
(4)large effect size (d>0.8).

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