

The serve clock reduced rule violations, but did not speed up the game: A closer look at the inter-point time at the 2018 US Open

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ABSTRACT

After treating time rule violations as a trivial offense over the past, tennis associations in 2018 permanently introduced an on-court serve clock to make sure that players do not exceed the time limit between points. In this study, we investigated the influence of this technological officiating aid at its first use in Grand Slam tennis at the 2018 US Open. By investigating time intervals between 2135 points at the Men's single tournament we found that the share of rule violations decreased (26.3%), but the average time did not (21.6 s) compared to previous studies. We could further confirm that the players still use this time interval for tactical reasons and to recover after longer rallies. In addition, the umpires, which do not show any reputation bias, have a significant influence on the inter-point time as well. Based on these findings we suggest introducing a serve clock that is started automatically. Further, we argue that a dynamic time limit, which takes the intensity of the previous rally into account, would be more appropriate. Players could be granted more time for recovery after longer rallies, but less time after shorter ones in order to reach the intended goals regarding pace of play.

Keywords: Time rule; Umpiring; Serve clock; Technological officiating aids; Tennis.

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INTRODUCTION

To ensure entertainment and attractiveness of tennis to a broad spectrum of fans as well as to fulfil the expectations of TV broadcasts, several rule changes were performed in the last years. In 1970 the tie-break was introduced to adjust the length of matches. Newer rule adaptations are “no-ad” scoring, the match tie-break in doubles and short sets at some special events (combined with a match tie-break). Using mathematical simulations, Pollard and Noble (2002) could show that best-of-five short sets until 4 games compared to traditional best-of-three tie-break sets lead even to an increase in the expected number of points played, whereas “no-ad” scoring and replacing the final set with a match tie-break until 10 points both reduced the expected number of points. Therefore, the length of tennis matches is shortened by using the latter formats. The most recent approach to make tennis even more attractive was tested at the ATP Next Gen Finals including changes like linesmen being replaced by the instant use of the Hawk-Eye technology and applying Fast4 as match format. Using Fast4 (best-of-five sets) scoring means that already at 3 games all a short set tie-break (deciding point at 4 points all) is applied and reduces the match time compared to three traditional tie-break sets (Simmonds and O’Donoghue, 2018).

In addition, a shot clock to count down the time between points was used (hereinafter referred to as serve clock). Before that, violations of the respective rule could be assumed as so-called *trivial offenses*. Kolbinger and Stöckl (2019) introduced this term for minor rule violations that are almost never penalized by officials. The treatment of time violations in tennis fulfilled the criteria described by them, as it was shown in the study of (Kolbinger, Großmann, & Lames, 2019). The time rule was violated for 58.5% of the serves, with only 0.1% of the violations being penalized. The introduction of the serve clock can be seen as a reaction to the inappropriate handling of the rule.

After its test at the ATP Next Gen Finals, the serve clock was introduced during the US summer swing 2018 on the ATP/WTA tour with its Grand Slam debut at the US Open. Further, the serve clock was implemented in the 2019 rule books of the WTA and ATP and is stepwise going to be mandatory at all WTA and ATP Tour events from 2020 on, starting with the Premier and Master events already in 2019. At least two serve clock panels must be visible on the courts for players and the chair umpire (ATP, 2019; WTA, 2019). At the moment, the usage is as followed: the chair umpire enters the point, announces the score and afterwards starts the serve clock. The players need to start their serving motion within 25 seconds, otherwise a time violation is given by the chair umpire. Still, the chair umpire can pause and resume or reset the serve clock if appropriate (ATP, 2018). This procedure is in contrast of the continuous play rule (Rule 29) in tennis of the ITF, where only maximum of 20 seconds is conceded towards the players from the moment the ball is out of play until the next serve is hit (ITF, 2019). However, in the Grand Slam, ATP and WTA rulebooks 25 seconds are allowed between points (ATP, 2019; Grand Slam Board, 2019; WTA, 2019).

The intention of the serve clock, according to Gayle Bradshaw (ATP’s executive vice president of rules and competition), is on the one hand to speed up the pace of play (USA Today Sports, 2018). This is in accordance with the main goals of rule modifications identified by Arias et al. (2011), which are to attract spectators and to fulfil commercial pressure and interests. However, rule modifications in sports should already be investigated before their final introduction, but there are only few studies analysing the effects of rule modifications and their results are often conflicting each other (Arias et al., 2011). The effect and intention of the serve clock was for example questioned by Kovalchik (2018) even before its introduction, as the time between the points was raised from 20 to 25 seconds and the average time between points was found to be below the new limit.

As the second intention of the introduction, Bradshaw pointed out that the serve clock should help the chair umpires to enforce the rules regarding the time between points (USA Today Sports, 2018). Up to now, the chair umpire was the only one to see the time running between points and it was upon his decision to penalize a player for being too slow. The serve clock as a visible tool for everyone makes these penalizations transparent to players and spectators. Therefore, the serve clock can be considered as a technological officiating aid (hereinafter: TOA) that should help the referee to enforce a rule according to the introduced taxonomy of TOA by Kolbinger and Lames (2017).

Adding the responsibility to start and pause the shot clock to the chair umpire's duties does not eliminate the potential for decisions affected by biases. Whereas there are no studies about bias in tennis umpiring, there is a huge body of literature about bias in sports. In baseball, Parsons et al. (2011) could show an effect of ethnicity on the decisions of the referee and behaviour changes of the player when knowing who is umpiring their game. Mills (2014), in addition, reported umpires to be more favourable with players who are more experienced and have a higher reputation. Another type of reputation-based bias was found by Kim and King (2014), who showed how the umpires adapted their judgements based on specific player's characteristics. Those kinds of bias can be transferred to tennis and the decision of the chair umpire to be more lenient with higher ranked players and allowing them more time, especially if those top players have a reputation of having extensive service routines. Another cause of referee bias is the size and composition of the supporting crowd as well as the distance between the crowd and the referee (Dohmen and Sauermann, 2016). In tennis, however, supporting crowd as such is only found in Davis and Fed Cup matches. Therefore, this effect may only play a minor role in affecting the chair umpire's decision. Nevertheless, the crowd size varies a lot from the big stadiums towards the small side match courts.

In this recent study the aim was to take a closer look at the time between the points at the US Open 2018 and investigate a possible influence of the serve clock. Kolbinger et al. (2019) already investigated the time between points at the Australian Open 2016 and the effect of several factors influencing this time interval. They reported an impact for the serving player, the previous rally length, service game, scoring streak, and importance of points. They further criticized the enforcement of the time rule as they found a high percentage of violations not being penalized. Therefore, they suggested a TOA, like the serve clock, to improve the enforcement of the rule. In general, the existing observational system of their study is used, but the analysed parameters are going to be extended by putting an additional focus on the chair umpire. An impact on the average time between points due to the serve clock is expected. It is assumed that more time violations against the players are awarded as each time the serve clock runs down to zero should be penalized and this fact is transparent by having the serve clock on the court. In addition, the chair umpire's behaviour and his contribution are observed.

METHODS

Sample

Data of 18 matches of the 2018 US Open Men's single tournament was collected by two experts, using the ordinary broadcasting signal of Eurosport (expert 1: 7 years' professional experience as chair umpire; expert 2: ten years' experience as sports analyst). 25 different players with an average ATP ranking of 48.8 (SD: 40.6) appeared in those matches, including four of the five top ranked players and five former Grand Slam champions. The well-proven observational system of Kolbinger et al. (2019) was applied to extract the serving player, the receiving player, the current score, whether it was a first or second serve, the number of strokes in each rally, the winner of the respective rally and the inter-point time. For all but two matches, we did not just record this total time between the points according to the official rules, which is starting with the moment

the ball was out of play, meaning that either the ball bounced twice or the trajectory of the ball ended in the net or out of bounce, and stopping with the moment the player actually struck the ball in order to conduct a serve (*Time*). In addition, we adapted our system to the implementation procedures for the serve clock. In detail, we collected two interval times, split by the moment the umpire announces the score, which represents the start of the serve clock, according to those procedures. This should enable us to measure the elapsed time after the start of the serve clock and therefore identify actual rule violations (*SplitTime2*), but also to explore patterns affecting the time it takes until the umpire starts the serve clock (*SplitTime1*).

Only inter-point times for which the time rule applies were observed, which excludes the first serve of each service game, second serves and serves in a tie break at odd scores or if the players changed sides. Further, we excluded serves that were preceded by one of the following events: Overruled decision by the umpire, Hawk-Eye challenge, change of any sort of equipment by one player, umpire demands the audience to be quiet, discussion between the umpire and one player and warnings. Thus, the observed 2834 rallies led to 2135 inter-point times that were eligible for this study and were used for the analysis in two different sets of data. Sample ONE included all inter-point times, sample TWO consisted of all matches, for which we were able to collect the two different split times (1692 inter-point times).

Reliability

To obtain the inter-rater agreement, both experts collected data of the same one hundred serves. Cohen's Kappa was calculated for nominal data, whereas correlation coefficients and further descriptive statistics were used to rate the agreement for the metric variables (the different split times for the inter-point time and the number of strokes per rally). All nominal variables showed a perfect inter-rater agreement (Cohen's Kappa equals one for each). Regarding the number of strokes, the correlation coefficient was 1.00, with a classification rate of 99.0%. For the overall inter-point time, as well as for the splits, the correlation coefficients also reached 1.00. The mean absolute difference was 0.14 seconds for the total time, 0.07 seconds for the first split time and 0.11 for the second split time. The biggest difference between the two observers was 0.8 seconds.

Data processing

The data collected by the self-designed observational system was processed to provide additional information and fit the data for statistical analysis. The variables *PrevRL* (number of strokes in the previous rally), as well as the dependent variables *SplitTime1* (time elapsed until the umpire announces the score), *SplitTime2* (time between score announcement and serve hit) and *Time* (total inter-point time) could be used without further preparation.

The current score was used to extract the variables *Set* (current set), *Game* (current service game), the dummy variable *Tiebreak* (equals 1 if true, and 0 otherwise) and the current scoring *Streak*. The variable *Streak* equals the number of points won or lost in a row by the serving player in a service game, prior to the start of the respective inter-point time. Due to the scoring system in tennis, the variable ranges from -4 to +4, as there is no scenario possible in which there is another serve if one player wins five points in a row in a service game. Further, similar to the study of Kolbinger et al. (2019), we labelled all scores as *Important Points* in which the receiving player was less than one point away of gaining a break ball (which includes actual break points) or the serving player had exactly one game point.

The player variables were transformed into n-1 dummy variables, equalling one if the respective player performed the serve and zero if not. The same scenario was applied for umpires and courts. We expect inter-individual differences for umpires, courts and players, but are not interested in generating knowledge about

an increase or decrease of the inter-point time that is affected by player x or umpire y . Thus, we created variables that equal the respective average (split) times per player, umpire and court: *PlayerMean1* (time until the umpire announces the score), *PlayerMean2* and *PlayerMean* (total inter-point time), as well as *UmpireMean1*, *UmpireMean2*, *UmpireMean*, *CourtMean1*, *CourtMean2* and *CourtMean*. This transformation was performed for players in Kolbinger et al. (2019) and led to no significant changes in the goodness of fit and the partial derivatives. However, we repeated those checks for the models used in this study.

All the dependent variables were z-transformed before they were included in the regression models, as were the predictor variables *PrevRL*, *Streak*, *PlayerMean1*, *PlayerMean2*, *PlayerMean*, *UmpireMean1*, *UmpireMean2*, *UmpireMean*, *CourtMean1*, *CourtMean2* and *CourtMean*. For *Game* and *Set* we decided that it is more appropriate to include the variables in the original form, as this allows to interpret the coefficients of those predictors as decrease or increase of the dependent variables per service game or set respectively. The dummy variables were not standardized as well.

Statistical analysis

In addition to descriptive statistics to investigate the patterns of inter-point times and the prevalence of rule violations, we ran regression models based on our two sets of data. For sample ONE we conducted one model with seven predictor variables: *Game*, *Set*, *Streak*, *PrevRL*, *Important Point*, *Tiebreak* and *PlayerMean*, which substitutes the dummy variables for the different players. The dependent variable is the total inter-point time (*Time*), which allows direct comparisons with the study of Kolbinger et al. (2019).

$$Time_i = \beta_0 + \beta_1 PlayerMean_i + \beta_2 Game_i + \beta_3 Set_i + \beta_4 Streak_i + \beta_5 PrevRL_i + \beta_6 Important\ Point_i + \beta_7 Tiebreak_i + \varepsilon_i$$

Based on sample TWO, we ran three models, one for each of the three dependent variables (*Time*, *SplitTime1*, *SplitTime2*), for which we add the respective variables for umpires and courts. Modell II adds the variables *UmpireMean* and *CourtMean* to Model I.

$$Time_i = \beta_0 + \beta_1 PlayerMean_i + \beta_2 Game_i + \beta_3 Set_i + \beta_4 Streak_i + \beta_5 PrevRL_i + \beta_6 Important\ Point_i + \beta_7 Tiebreak_i + \beta_8 UmpireMean_i + \beta_9 CourtMean_i + \varepsilon_i$$

In addition, we computed the same model for both split times. Thus, *SplitTime1* serves as dependent variable for Modell III and *SplitTime2* as dependent variable for Modell IV. Consequently, we substitute the variables *PlayerMean*, *UmpireMean* and *CourtMean* by *Player/Umpire/Court*MeanSplit1* and *Player/Umpire/Court*MeanSplit2* respectively.

$$SplitTime1_i = \beta_0 + \beta_1 PlayerMeanSplit1_i + \beta_2 Game_i + \beta_3 Set_i + \beta_4 Streak_i + \beta_5 PrevRL_i + \beta_6 Important\ Point_i + \beta_7 Tiebreak_i + \beta_8 UmpireMeanSplit1_i + \beta_9 CourtMeanSplit1_i + \varepsilon_i$$

$$SplitTime2_i = \beta_0 + \beta_1 PlayerMeanSplit2_i + \beta_2 Game_i + \beta_3 Set_i + \beta_4 Streak_i + \beta_5 PrevRL_i + \beta_6 Important\ Point_i + \beta_7 Tiebreak_i + \beta_8 UmpireMeanSplit2_i + \beta_9 CourtMeanSplit2_i + \varepsilon_i$$

All models were compared to models in which we substituted the variables showing the average times for players, umpires and courts with the respective dummy variables. The severity of multicollinearity was measured using the variance inflation factor (VIF). Data collection and processing was performed with

Microsoft Excel 2016 (Microsoft, Redmond, USA). Data transformation and all the statistical analysis were conducted in R (R Development Core Team, 2015).

RESULTS

Prevalence of rule violations

The average inter-point time at the 2018 US Open was 21.6 seconds (SD: 5.2), with 26.3% of those intervals exceeding 25 seconds (see Figure 1a). As the implementation procedures of the serve clock states that the 25 seconds interval of matter for the time rule starts with the announcement of the score, a special interest was on this split time. The mean duration of *SplitTime2* was 19.3 seconds (SD: 4.7) and the number of actual rule violations was 213 (12.6%) (see Figure 1b). Only two (0.9%) of those violations were penalized.

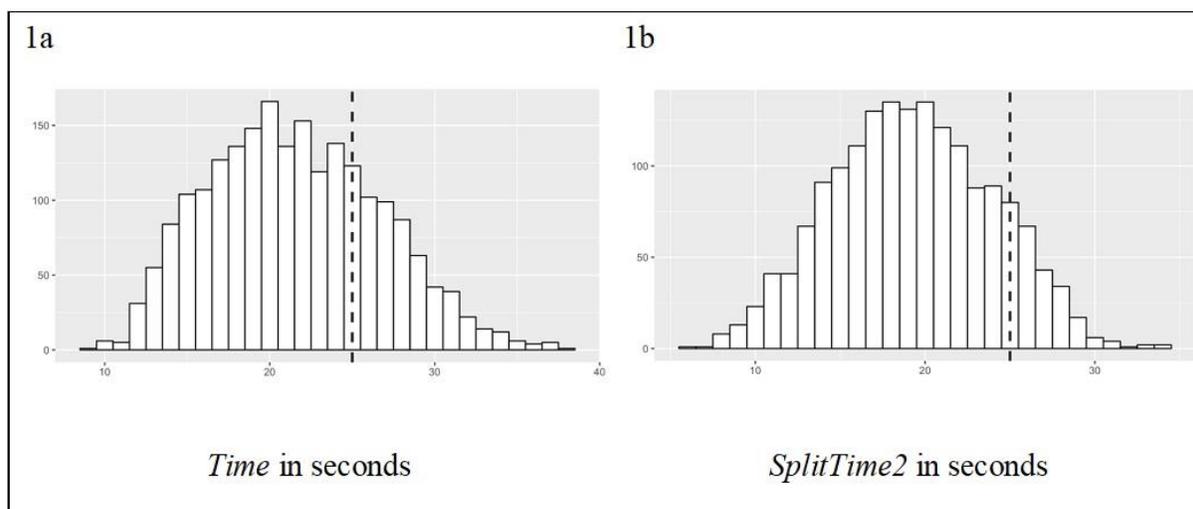


Figure 1. Histograms for the total inter-point time (*Time*) and the time elapsed after the umpire announced the score (*SplitTime2*). The dashed line marks the permitted 25 seconds interval.

Influence of the predictor variables on *SplitTime1*, *SplitTime2* and *Time*

We structured the reporting of our models based on the variables, as we wanted to look for specific patterns for the different time intervals. The respective models are listed in Table 1 and Table 2.

Concerning predictors that describe the chronological point of time in a match, *Game* and *Set* show significant correlations with *Time* and *SplitTime2*, but all coefficients are below the 0.1 threshold for weak correlations. *Game* further serves as a significant predictor in all of our models, whereas *Set* does not show any individual influence on *SplitTime1*. Whether a point is played in a *Tiebreak* or not shows an individual influence on the dependent variable in all models. The total-inter point time in *Tiebreaks* is 0.73 standard deviations higher than in regular service games, the split time until the umpire announces the score increases by 0.40 standard deviations, and those after the announcement by 0.59. *Important Points* show the same pattern, serving as significant predictors for *Time* (coefficient of 0.55), *SplitTime1* (0.31) and *SplitTime2* (0.47).

Streak is the only predictor that shows a substantial negative correlation for *Time* and *SplitTime2*. Thus, the respective time intervals increase with decreasing values of *Streak*. We illustrated this pattern in Figure 2. For all cases in which the server has a positive streak the inter-point time is lower than for those cases in

which the receiving player won the last point or couple of points respectively. This effect is smallest for *SplitTime1*. *Streak* serves as a significant predictor in all models.

Table 1. Correlation coefficient with the inter-point time for all variables included in the summarized models *Time I* and *Time II*.

	Correlation with <i>Time</i>	Model <i>Time I</i>	Model <i>Time II</i>
	R ² (t-value)	Coefficients (t-value)	
PrevRL	.459*** (23.9)	0.363*** (25.5)	0.388*** (24.9)
Game	.081*** (3.74)	0.032*** (6.69)	0.035*** (6.81)
Set	-.059** (-2.73)	-0.048*** (-3.53)	-0.049** (-3.26)
Important Point	.301* (14.6)	0.530*** (17.6)	0.554*** (16.6)
Tiebreak	.106*** (4.94)	0.710*** (5.55)	0.728*** (5.49)
Streak	-.241*** (-11.5)	-0.120*** (-8.08)	-0.114*** (-6.96)
PlayerMean	.557*** (30.9)	0.530*** (37.7)	0.478*** (24.2)
UmpireMean	.414*** (18.7)		0.105*** (5.27)
CourtMean	.194*** (8.12)		-0.049** (-2.88)
Intercept		-0.304*** (-6.71)	-0.326*** (-6.66)
Goodness of fit			
F (df, n)		434.6*** (7,2127)	292.4*** (9,1682)
R ²		.589	.610
Adjusted R ²		.587	.608

Note: * = $p < .05$; ** = $p < .01$; *** = $p < .001$.

Table 2. Correlation coefficient with the respective time intervals for all variables included in the summarized models *SplitTime1* and *SplitTime2*.

	Model <i>SplitTime1</i>		Model <i>SplitTime2</i>	
	Correlation R ² (t-value)	Coefficients (t-value)	Correlation R ² (t-value)	Coefficients (t-value)
PrevRL	.419*** (19.0)	0.385*** (19.0)	.316*** (13.7)	0.242*** (14.4)
Game	.019 (.79)	0.020** (2.98)	.069** (2.85)	0.028*** (5.18)
Set	.006 (.27)	0.019 (1.00)	-.086*** (-3.55)	-0.057*** (-3.48)
Important Point	.202*** (8.50)	0.309*** (7.10)	.246*** (10.4)	0.466*** (13.0)
Tiebreak	.046 (1.91)	0.398* (2.30)	.099*** (4.08)	0.588*** (4.12)
Streak	-.081*** (-3.33)	0.050* (2.33)	-.226*** (-9.52)	-0.150*** (-8.48)
PlayerMean	.059* (2.41)	0.053 (1.38)	.564*** (28.1)	0.520*** (24.2)
UmpireMean	.091*** (3.76)	0.312*** (9.47)	.410*** (18.4)	0.143*** (5.71)
CourtMean	.075** (3.07)	0.013 (.48)	.177*** (7.37)	-0.040 (-1.94)
Intercept		-0.283*** (-4.47)		-0.237*** (-4.49)
		Goodness of fit		Goodness of fit
F (df, n)		96.4 (9,1682)		225.6 (9,1682)
R ²		.340		.547
Adjusted R ²		.337		.545

Note: * = $p < .05$; ** = $p < .01$; *** = $p < .001$.

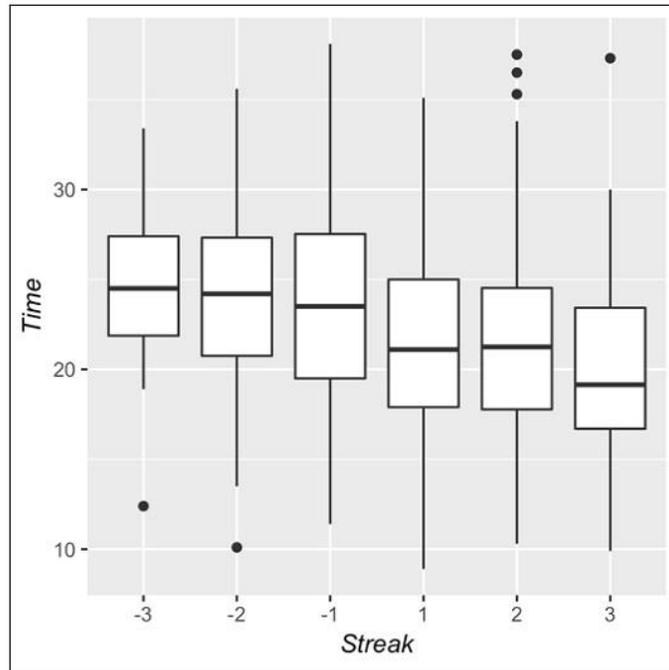


Figure 2. Boxplot for the total inter-point time (*Time*) in relation to the scoring streak.

The variable that shows the highest correlation with *SplitTime1* is *PrevRL* ($r = 0.42$, $t = 19.0$, $p < .001$), which is also one of the two variables that has a higher influence on this first split time, from the moment the ball is out of play until the announcement of the score, compared to the second split time. However, it serves as a highly significant predictor for all models, with each increase of the number of strokes by one standard deviation (3.8 strokes) leading to an increase of the duration by 0.39 (*SplitTime1*), 0.24 (*SplitTime2*) and 0.39 (*Time*) standard deviations respectively.

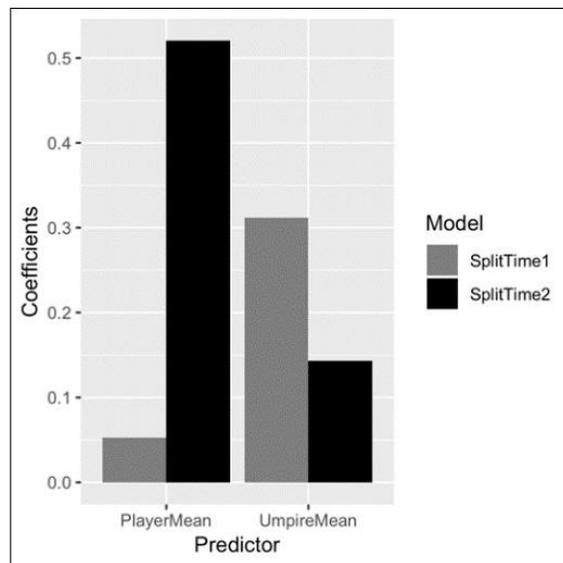


Figure 3. Coefficients for *PlayerMean* and *UmpireMean* for the models for *SplitTime1* and *SplitTime2*.

PlayerMean is the most important predictor for *SplitTime2* and *Time*, and also shows the highest correlations with those dependent variables (*SplitTime2*: $r = 0.56$, $t = 28.1$, $p < .001$; *Time*: $r = 0.56$, $t = 30.9$, $p < .001$). For *SplitTime1* this variable not even has a weak correlation and does not serve as a significant predictor after we control for other variables (Figure 3).

UmpireMean, as does *PrevRL* (see above), has a greater influence of on the first split time than on the second split time (Figure 3). However, it serves as a significant predictor in all models, in which this variable was included. *CourtMean* has a weak to medium correlation with *SplitTime2* as well as *Time* and is a significant predictor in the model for the latter.

DISCUSSION

Prevalence of rule violations

The average inter-point time of 21.6s found at the 2018 US Open was slightly higher compared to other studies. Kolbinger et al. (2019) measured an average time between points of 21.5s at the Australian Open 2016. Kovalchik and Albert (2017) in contrast found the time-to-serve at 19s for male players at the same tournament. A possible explanation may be the fact that they excluded all time segments above 34s whereas Kolbinger et al. (2019) only excluded inter-point-times with special events occurring. O'Donoghue and Liddle (1998) reported 19.2s at the French Open and 18.4s at Wimbledon in 1996. The US Open 2018 differed from the others as the players were allowed to take 25s between points instead of 20s. On the one hand, the serve clock, used for the first time at Grand Slam tennis at the 2018 US Open, still did not speed up the play as the inter-point time did not decrease. On the other hand, the five seconds raise in time allowed between points did not lead to an increase in the time between points at Grand Slam Tournaments.

Time rule violations (inter-point time above 20s) occurred for 58.5% of all inter-point times observed at the Australian Open 2016, with only 0.1% of those being penalized as time violations (Kolbinger et al., 2019). In this study, with the new ruling applied, the *SplitTime2* was on average 19.1s and the frequency of time rule violations decreased to 12.6%. Only two of those incidents (0.9%) were penalized. Keeping in mind the rule change to allow players 25s nowadays, we have to compare this number with the number of interruptions exceeding the previous allowed time by more than 5s in the study of Kolbinger et al. (2019), which was 24.8%. Taken this into account, it seems that the number of violations halved itself, but the numbers need to be treated with caution. The applied procedure took the score announcement as starting point, but this may differ from the moment the chair umpire starts the serve clock. Further, in accordance with the official rules, *SplitTime2* was measured until the serve was hit instead of until the start of the service motion. Hence, we took a separate look at those cases exceeding the time limit by more than 2s. As a consequence, the percentage number of time violations dropped to 5.8% and penalizations raised to 2.1%. However, the fact that *SplitTime2* exceeded 25s in a high number even by more than 2s without being penalized, even supports the concerns about the appropriate application of the serve clock. The small number of awarded time violations indicates that either chair umpires start the serve clock late, mark the start of the next point before the players start their service motion or just do not penalize players even if the clock ran down to Zero (visible for all stakeholders).

Influence of the predictor variables on *SplitTime1*, *SplitTime2* and *Time*

The increasing influence of *PrevRL* on *Time* and *SplitTime2* can be seen as a physiological factor. Players seem to take the time between points as a chance to recover from exhausting rallies. Kovalchik and Albert (2017) also detected longer preparation times for players with increasing rally length of the previous point. The increasing influence on *SplitTime1*, which represents the time until the chair umpire makes the score

announcement, might be due to two reasons. On the one hand, they are maybe aware of the physiological factor of a long-lasting previous rally on the players and allow them more time. On the other hand, long rallies are often also more spectacular than an early unforced error and the crowd applauds louder, sometimes animated by the players who celebrate their points. Therefore, the chair umpire waits a few seconds longer to calm down the crowd to be able to make an announcement hearable for everyone.

In contrast, the factor *Game* increasing *Time* as well as both *SplitTimes* seems to hark back more to the importance of points towards the end of the set than physiological demands, as for *Set* the coefficient shows a slightly negative influence, which indicates that the time between points does not just increase because the overall duration of a match increases. Kolbinger et al. (2019) came to the same conclusion, stating that lost service games in the late stages of a set put a player into more trouble, as less or no time is left to re-break the opponent. In addition, Maquirriain et al. (2016) concluded that professional tennis players are able to overcome ongoing fatigue and maintain a constant serving speed throughout a five-set-match, when comparing the first and the final set. As in Kolbinger et al. (2019), *Important Point* and *Tiebreak* also indicate that players tend to take more time under pressure and in the crucial time of a match. Kovalchik and Albert (2017) also found longer preparation times associated with increased point importance.

Streak tend to reflect the patterns described above. The more pressure is on the serving player the more time he takes. He might be thinking more about tactical components for the next point but could also try to stop the rhythm of the opponent. In other sports time outs are often used to stop a negative flow of game (e. g. in handball (Halldorsson, 2016)). In tennis – except for medical reasons - there shall not be any timeouts and so prolonging the time to start the next point is the only possibility for tennis players to disrupt the rhythm of their opponents. This observation goes along with the findings and conclusions from the study of Kolbinger et al. (2019).

The individual habits of a player show the highest correlation with *Time* and *SplitTime2*, indicating differences in the time the players take to serve. These results coincide with the wide-spread perception of different player types on the tour. Fast serving player's like Federer and Kyrgios contrast with slow paced players like Nadal or Djokovic who have extensive rituals before they serve. The same evidence was found by Kolbinger et al. (2019). Moreover, Kovalchik and Albert (2017) as well detected large variations among different players, varying from 15s to 25s. Their findings further showed that variation between player's is smaller than within, leading to the assumption that all players react in the same way to influencing factors on their service routines. Interestingly, *PlayerMean* does not influence *SplitTime1*. Thus, the chair umpire seems not do adapt his routines based on the reputation of a player.

Taking a closer look at the influence of the chair umpire, it could be shown that the average time until score announcement differed by more than 2s between chair umpires (*UmpireMean1*). As a consequence, players are allowed to take more time between points depending on the chair umpire automatically, as the serve clock is started later. Interestingly, an increase in *UmpireMean* also leads to an increased *SplitTime2*. This means player do not have their consistent routines between points or orientate themselves always at the same time on the serve clock running down independent from the chair umpire. Instead, a player seems to take even more time to prepare if one umpire is slower than another to start the serve clock.

Summarizing the results for *SplitTime1*, the conclusion that the chair umpire – hopefully unconsciously – has an impact on the time between points is supported. Umpires seem to be aware of the score and the match situation – indicated by the variables *PrevRL*, *Game*, *Important Points* and *Tiebreak* – and adapt their behaviour correspondingly. This influence of the match situation on the timing of the score announcement

indicates a temporal variance in the handling of the rule. Temporal variance describes the varying application of rules under certain circumstances or during different period of a match, especially in the crunch-time. The factors *Game*, *Important Points*, *Tiebreak* and *PrevRL* suggest a deviant behaviour from the chair umpires which can be interpreted as temporal variance. Berman (2010) favours a temporal variant handling and applying of rules. In his opinion, only the athletic skills should decide a close game. Standen (2013), in contrast, criticizes a different application of rules, as rules are rules and those do not change during specific (important) parts of a competition. He highlights that temporal variance takes away the competitive benefit from one team and saves the offender from being penalized.

CONCLUSION

To conclude, the actual procedure of the application of the serve clock gives rise to some questions. First, whereas the share of rule violations decreased, the aim of the tennis associations to speed up the game could not be achieved. Regardless of the goal not being achieved, a serve clock though seems appropriate to speed up the time of play as most of the time in tennis matches is spend in preparation of the serve (Kovalchik, 2018; O'Donoghue and Liddle, 1998). Further, the study provides evidence for the chair umpire directly and indirectly influencing the time between points. Umpires were found to vary the time until they start the clock according to the match situation (temporal variance). In addition, umpires showed significant individual patterns, for example starting the serve clock slower than other umpires, to which players adapted by taking even more time until they start the next point. This start of a point, determined by the start of the serving motion, is also vaguer defined than in the official rules (moment of the ball being hit).

Based on these findings, we argue that the duty of starting the serve clock should be transferred from the chair umpire to a technological officiating aid (TOA). The widespread use of tracking technologies would enable the tennis associations to perform this change without significant costs, as those TOAs are able to determine the end – as well as the start – of a rally. This would avoid a possible favouritism of a player depending on the match situation. Further, as it was already suggested by Kolbinger et al. (2019), the TOA could be used to introduce a dynamic time limit coupled to the previous rally length. This physiological factor is the only one that plays a comparable role to both players, so an adaption based on this would not favour one of the players in some way.

AUTHOR CONTRIBUTIONS

Alexander Mühlberger conceived the study design, collected the data, contributed to the statistical analysis, and drafted the manuscript. Otto Kolbinger conceived the study design, performed the statistical analysis and drafted the manuscript. Both authors read and approved the final manuscript.

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