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GENDER COMPARISON OF IN-MATCH PSYCHOLOGICAL TRAITS OF TENNIS PLAYERS: DYNAMIC NETWORK ANALYSIS

Antonina Milekhina[1]
Higher School of Economics, Moscow, Russia - ORCID 0000-0002-4188-4557

Kristijan Breznik
International School for Social and Business Studies, Celje, Slovenia - ORCID 0000-0002-8136-9592

Marialuisa Restaino
University of Salerno, Fisciano, Italy - ORCID 0000-0002-1150-8278

Abstract This study aims to investigate the existence of professional tennis players' psychological traits. For this purpose datasets on tennis matches of professional male (ATP) and female (WTA) tennis players were collected. Dynamical network analysis was applied with the RSiena program. Results revealed differences in in-match psychological characteristics' influence on the ability to build positive head-to-head for male and female players. Furthermore, a revealed tendency of head-to-head networks to cyclic structures is discussed. The study represents one of the first attempts to explore sport-related content with tools of dynamical network analysis.

Keywords: *tennis, gender comparison, match analysis, dynamic network analysis, RSiena.*

1. INTRODUCTION

Data analytics is growing its popularity due to the rapid development and increasing availability of big data. The possibility of large amounts of information is creating more and more opportunities for organizations and individuals for making use of and processing them.

Over the years, various approaches have been adopted for analyzing both the results of sports matches and competitions and the performance of teams and individual athletes in numerous sports.

Among other sports, tennis stands out for some reasons. First of all, tennis is a mostly individual sport, which means that the results could be attributed to the

[1]Corresponding author: Antonina Milekhina, antonina.milekhina@yandex.ru

player as opposed to team sports, where team success should take into account the efforts of each team member. The second feature of tennis is the fact that a tennis match is played till the last point is won. Therefore, there is no time restriction for a match and comebacks are not unusual in tennis matches. Thus, psychological momentum plays important role in a champion's mind setup.

Third, a tennis player's career is usually relatively long and can span over fifteen-twenty years. Also, there are cases when athletes achieved a peak in their career towards their end. Fourth, tournaments of different calibers are played almost every week. So we have weekly ranking updates and the opportunity to follow one's career changes in tiny pieces for a long period of time. Ranking updates provide information about players' progress within the calendar year and in the latest 12 months.

This provides us with a good opportunity to study career trajectory and explore mechanisms of its development, also taking into consideration that ranking and head-to-head information only can be misleading due to the incompleteness of its information.

This study aims to investigate the existence of professional tennis players' psychological traits. And if this trait exists, gender comparison would be additionally explored.

The rest of the paper is structured in the following order. In Section 2, we provide a comprehensive literature review of the topic. After the Literature review, a description of networks and models with additional information is provided. Data collection and a brief descriptive data overview are reported in Section 4. The main results of analyzed networks and network models with Discussion are presented in Section 5, followed by Conclusions.

2. LITERATURE REVIEW

There is a lot of literature on investigating tennis matches and players' results, and exploring the differences and similarities between male and female players by looking at the various aspects of a match.

Short-termly player's results have been largely examined on the level of point, match, and tournament (Klaassen and Magnus, 2001; Knottenbelt et al., 2012; O'Donoghue and Brown, 2009; Ovaska and Sumell, 2014; Serwe and Frings, 2006). In particular, Klaassen and Magnus (2001) focused on predicting the winner of a point in a match. They showed that the probability of winning a point is not random and win of the previous point has a positive effect on winning the current. Then, O'Donoghue and Brown (2009) argued that the sequence of points that occur in a tennis match does not differ from random, leading to a discussion of psychological momentum and its impact on one's game. In fact, as outlined in the research of psychological momentum (PM) by Iso-Ahola and Dotson (2014), if initial success leads a competitor to perceive *Self* as the superior performer (e.g., higher competence) and concurrently *Opponent* as the inferior performer, positive PM is likely to occur and success to ensue. On the other hand, if the Self-Opponent perceptions are reversed following the initial performance, negative PM is experienced and downward spiraling performance is likely to follow. Finally, when the perceptions are closely matched, neither competitor achieves PM (Iso-Ahola and Dotson, 2014).

For analyzing and predicting the outcome of the match, different regression models and machine-learning algorithms have been adopted (Candila and Palazzo, 2020; Jayal et al., 2018; Lisi and Zanella, 2017; Sipko and Knottenbelt, 2015). In Candila and Palazzo (2020), the artificial neural networks (ANNs) were implemented to forecast the probability of winning in tennis matches, while in Lisi and Zanella (2017) the logistic regression was estimated for predicting the winner.

An interesting field of research deals with examining long-term career trajectories of tennis players by using rankings (Kovalchik et al., 2017; Li et al., 2018; Lisi and Zanella, 2017). In Kovalchik et al. (2017), it was found a strong association between the shape of the ranking trajectory and the highest career ranking earned. Then, for evaluating ranking trajectory some important marks in a player's career were analyzed (e.g., age of first being ranked, age of achieving top-100, et cetera) (Li et al., 2018).

Moreover, different approaches have been proposed for evaluating and analyzing the ranking of players, such as paired comparison of players (Baker and McHale, 2014; Kovalchik, 2020; McHale and Morton, 2011), incomplete pairwise comparison (Bozóki et al., 2016; Szàdoczki et al., 2022), sorting algorithms (Spanias and Knottenbelt, 2013). Then, a broad discussion is also on whether the current ranking rules are fair and represent the true level of the player and whether ranking could be a good predictor for match results (Del Corral and Prieto-Rodriguez, 2010; Dingle et al., 2012). Further, probit regression has been implemented by Del Corral and Prieto-Rodriguez (2010) for the prediction of outcomes in tennis matches based on the ranking difference between two players.

Finally, some studies have proposed to apply tools of social network analysis for establishing players' hierarchy and creating alternative ranking systems, e.g. Subgraph-Based Ranking (Aparício et al., 2016; Maquirriain, 2014; Spanias and Knottenbelt, 2013), link analysis of Hubs and Authorities (HITS algorithm, Hyperlink-Induced Topic Search), simple PageRank and PageRank with teleportation (Michieli, 2018), time-dependent PageRank algorithm (Breznik, 2015; London et al., 2014; Radicchi, 2011) network-based dynamical ranking system (Motegi and Masuda, 2012). Moreover, the weighted networks are also used for predicting the probability of winning (Arcagni et al., 2022). These approaches were used to compare players' greatness, both concurrently and all-time (Radicchi, 2011).

An important recent issue in sports is to analyze whether there are differences and similarities between men and women (Blanca Torres, 2019; Cross, 2014; Cross and Pollard, 2009; Fernández-García et al., 2019; Hizan et al., 2011, 2015). The perspective of differences in various aspects of the game of tennis, e.g. the number of aces, double faults, unforced errors, winners, tiebreak sets, games per set, and points per game, was analyzed by Cross (2014). Then, Blanca Torres (2019) explored the differences in the duration of the match, the number of sets, and the duration of sets between junior and absolute categories and regarding the surface in both genders. It turns out that in the absolute category, there were no differences in the duration of the match, and in the duration and number of sets. Meanwhile, significant differences between genders were observed in the performance indicators between winners and losers in London 2012 Olympic Games tennis tournament (Fernández-García et al., 2019). Break points won was the most relevant prediction variable to the result of the match in the female category. In the male category, it was joined by first-serve points won and first-serve return points won. Then, still speaking of gender, players showed different serve patterns as men served not surprisingly faster, with higher success, and placed their serves more frequently to the external areas of the service boxes. Women's serve was directed more to the body of their opponent.

Another relevant topic when analyzing the difference between males and females lies in investigating patterns of hemispheric specialization for cognitive function and those patterns may be related to handedness (Lake and Bryden, 1976). In Vogel et al. (2003) and Rilea et al. (2004) it was proven that the difference in spatial ability scores between left-handed and right-handed persons has been higher among males compared to females. Meanwhile, Breznik (2013) asserted that the advantage of left-handed professional tennis players over their right-handed opponents is higher in males compared to females. Then, the quality of players and matches is inversely proportional to the advantage of left-handers against their right-handed counterparts.

Physical abilities are without a doubt crucial for a tennis player. However, physical abilities alone cannot explain the success or failure of some players. If a player's success were related only to physical abilities, predicting would be very much straightforward (faster, higher, et cetera will always win). We are aware of cases when players with smaller heights achieve great success against higher players or players with higher speed of serve. And thus we might assume that psychological traits contribute to a player's success as well, which was already stated by Morgan (1985) in his Mental Health Model.

In order to achieve success, a player should be mentally tough as summarized by Connaughton et al. (2008). Mental toughness is defined by Jones (2002) as "having the natural or developed psychological edge that enables you to (1) generally, cope better than your opponents with the many demands (competition, training, lifestyle) that sport places on a performer, and (2) specifically, be more consistent and better than your opponents in remaining determined, focused, confident, and in control under pressure."

Moreover, Jones (2002) ranks twelve mental toughness attributes. Part of them is lifestyle characteristics, which are out of focus for our research. Another part, however, could be attributed to the in-match mindset:

1. Having an unshakable self-belief in your ability to achieve your competition goals.

2. Bouncing back from performance setbacks as a result of increased determination to succeed.

3. Thriving under the pressure of competition.

4. Accepting that competition anxiety is inevitable and knowing that you can cope with it.

5. Not being adversely affected by others' good and bad performances.

6. Remaining fully-focused on the task at hand in the face of competition-specific distractions.

7. Pushing back the boundaries of physical and emotional pain, while still maintaining technique and effort under distress (in training and competition).

Though Jones (2002) describes this as "perception of the attributes of the ideal mentally tough performer", we might suggest that these characteristics can be expressed and inspected through match results. Unshakable self-belief (1) can represent the ability of a player to win against higher-ranked players. Thriving under pressure (3) and remaining fully-focused (6) correspond to the ability to win tough sets. Not being adversely affected by others' performance (5) can also be expressed by not losing easy sets.

Building together a network of tennis matches and the psychological traits of a player, we may suggest the following scheme to conceptualize our research: both the psychological traits of a player and his/her existing embeddedness into the current network influence result of a given match, which in turn influences the overall performance of one player against another one (one's head-to-head), which builds a directed link in the network. This affects network structure and leads to network evolution, which in turn changes the player's position in the network and thus the player's chances for success.

Based on the theoretical framework, we will focus on two main hypotheses with some sub-hypotheses below. Each of them will be tested separately for male and female competition.

Hypothesis 1: Relation of head-to-head match records between professional tennis players will show the tendency to transitivity.

This hypothesis can be postulated in the following way: if the head-to-head results of the first player to the second one are positive and the head-to-head of the second player against the third one is also positive, we to the same extend predict positive head-to-head result from the first player against the third one.

Hypothesis 2: The probability of creating the positive/negative head-to-head match record of one player against another player depends on his/her psychological traits and the psychological traits of his/her opponents.

Hypothesis 2a: The ability to thrive under pressure will enhance one's chance to build a positive head-to-head against other players.

Hypothesis 2b: Being prone to lose easy sets and matches will decrease one's chances against other opponents (to build outgoing ties in the network).

Hypothesis 2c: Ability to win against higher-ranked opponents will enhance one's head-to-head against other opponents.

3. NETWORK(S) AND MODEL DESCRIPTION

Social network analysis deals with a structural approach to interactions among social actors (Freeman, 2004). The building blocks of each social network are nodes and links (directed or undirected). Nodes are representing actors which are in our case tennis players. A relation is presented with a directed link (or an arc) and denotes the current match record between two tennis players in a network.

A match record constitutes a dyadic relationship being a result of previous interactions between two individuals with both of them contributing to it. In this sense, it's impossible to attribute the current head-to-head record to the action of one of the players as compared to e.g. runners' results. On the other hand, the match record is not the result of cooperation between two players (as in team sports). A dyadic relationship of two actors within one match record has competition in nature with the winner taking it all. This establishes the clear hierarchical structure of who is a better player in the dyad. Each further match between two actors contributes to dyadic relationship development, which can preserve current head-to-head or dissolve (by balancing it out). Putting such a relationship between several actors together we build a network of head-to-heads and observe its development from year to year.

We would expect that outline of such a network will follow the outline of a network built by a preferential attachment mechanism, which assumes that actors with a higher degree (or outdegree in our case) are easier to get another outgoing link (Newman, 2001). Indeed a player with higher outdegree is a player, who has better head-to-head records, also having a positive head-to-head with many players presumes winning many matches and thus potentially having a higher ranking. A player with a higher ranking is expected to be a better player and win against lower-ranked players. However, from time to time an unexpected link occurs when a lower-ranked player (so-called underdog) wins.

In such a network, the direction of the link is determined not only by the individual characteristics of both players but also by the whole structure of the network relationship, in which both of them are embedded. Network embeddedness was applied by Granovetter (1985) to market societies and described as "attempts at purposive action embedded in concrete, ongoing systems of social relations", but this mechanism is applicable in sport as well since we assume that wish to win is a purposive action. The network structure of two players can explain the direction of a potential link between them (which is who will win more matches between them and thus will have a positive head-to-head). As each new match potentially establishes a new link, the network of match records (and the network of head-to-heads as its derivative) is in constant evolution.

Due to the way tournaments are organized, tennis matches are very suitable for network modeling. The network is constructed so that the players represent the nodes, and the characteristics of their mutual matches describe the links between them. The first work that used network modeling in the field of tennis is represented by Situngkir (2007), where the network generation was introduced and explained, and then some analysis were performed on single Grand Slams tournaments matches only.

In order to analyze the evolution of the network of match records and dependencies within such evolution, the stochastic actor-oriented model (SAOM) suggested by Tom Snijders was applied (Snijders, 2001). SAOM's purpose is to explain the evolution of a network as a function of the structural effects of the network itself (e.g. reciprocity, transitivity, et cetera), actor variables (constant and varying), and dyadic variables (constant and varying). With help of SAOM, longitudinal networks for several snapshots of observations can be evaluated. SAOM are "actor-oriented", which means that they model change from the perspective of the actors, both focal actors (or egos) and their neighboring actors (or alters) (Snijders, 1996). Actors are active subjects with their goals constrained by the current network structure (Snijders, 1996). SAOM are continuous-time Markov chain models, allowing also to simulate the evolution of a network with given effects. The evolution of a network is regarded as the number of probabilistic sequential ministeps. A ministep implies an actor's action of creating, maintaining, or terminating outgoing tie. The transition between two waves of network observation consists of all ministeps done (Ripley et al., 2011). To explain changes in a network and in an actor's behaviour, different actor covariates and network effects can be used.

We propose the following network modeling setup: choose a time period (called a wave) for all steps (e.g. 3-year periods), then choose a starting point (e.g. 1 January 2001). A wave is built on three (accumulated) networks. The first network represents a head-to-head record at the end of the first year based on all match records for this year, the second network represents a head-to-head record at the end of the second year based on all match records for the first two years et cetera. Such an approach helps to gradually accumulate information about each period with no big jumps in the number and list of network participants. Participants from all networks are present in the SIENA model starting from the first one as per RSiena requirement. We can model those players who were not present as structural zeros, even if this is not obligatory. We can think of these players as present on tour and in this sense, they also had the opportunity to build a link in earlier networks but either willingly or due to some circumstances haven't done it. A link in a such network represents a head-to-head record of two players. The link will go from the player with more wins to a player with fewer wins in their match history for a particular period. If there is no match history between two players or their head-to-head is even, then there is no link. Such representation will give us information about who is a better player in the course of the time period and not only in a particular match.

In such a model setup, there is the possibility of both tie emerging (a player wins a match and a positive head-to-head emerges which is represented by outgoing tie) and tie dissolving (a player used to have a positive head-to-head, but loses a match and head-to-head balances out which is represented by tie dissolving). Thus we will evaluate network effects for the possibility of tie emerging, maintaining, and dissolving (function evaluation). Network evaluation function for player i is given by

$$f_i^{net}(x) = \sum_k \beta_k^{net} s_{ik}^{net} x \tag{1}$$

where β_k^{net} are parameters and $s_{ik}^{net} x$ are effects (Ripley et al., 2011). The equation (1) can be understood in a similar way as for instance multiple regression model equation. For each player, we can estimate his or her score with the linear combination of chosen effects. Varying effects used, we can produce several different models. The list of specific models used in our research with associated effects is presented below. For each model, associated coefficients β_k^{net} will be calculated by model estimation.

Due to limitations of calculating power because of the high number of actors in networks, we were forced to put covariate and network effects into separate models. We evaluate them for both ATP and WTA tours in separate runs. In order to build a model we introduce a notion of a wave. The wave is a time period included into one run of the model within which several shapshots of the network are taken and the development between each snapshot and the beginning of the wave is observed. This helps us to take into account both previous network setup and development for each year within one wave. We propose the following network modeling setup: (1) choose the length, starting point, number of snapshots per wave, number of waves per model, and lag between current and next wave starting points, (2) run the same SIENA model for all waves, (3) choose significant effects for most waves. Overall we estimated five models for each tour applied to ten waves of networks, each wave in turn consists of 3 consecutive years.

To test Hypothesis 1, we propose the first model which includes two network effects: transitivity and 3-node cycle effects. The transitivity effect (or transitivity closure) is a hierarchical effect and can be described as follows: an outgoing tie from node A to node B and from node B to node C increases the chance of an outgoing tie from node A to node C. Such effect presumes a clear understanding, of who is the best player in this triad. A cycle effect is the number of 3-node cycles a player is involved in. In other words, a cycle will emerge if player A has a positive head-to-head over player B, player B has a positive head-to-head over player C and player C has a positive head-to-head over player A. Such effect presumes no hierarchy in the triad. Moreover, it's impossible to single out the best player in the triad, which means that on-paper underdogs can win as well. Unfortunately, we were able to achieve convergence for ATP only for 6 waves out of 10 (1-5 waves and 8). Regarding the postulated Hypothesis 1 we expect in the first model tensity towards transitivity but not to 3-node cycles.

Hypothesis 2 with its sub-hypotheses was tested with the following four models (models two to five). The second model includes ego effects with creation function for all covariate effects included. With help of this model, we evaluated whether any included effects increase the chance of creating an outgoing tie (building positive head-to-head) for a player. Unfortunately, we were not able to achieve convergence for ATP data for this model, so we only discuss results for WTA data.

The third model includes alter effects with a creation function for all covariate effects. Hence we assess whether any of included effects increases the chance of incoming tie (or negative head-to-head) for ego.

The fourth model includes ego effects with endowment function for all covariate effects, thus we examine the chance that the tie will dissolve (or head-to-head is balanced out or reversed to the benefit of ego's opponents).

The fifth model includes alter effects with endowment function for all covariate effects. In other words, this model evaluates the chance that the incoming ties will dissolve (or head-to-head is balanced out or reversed to the benefit of ego).

It should be indicated that each year is unique and due to circumstances that happened (e.g. injuries of players, other outer circumstances), head-to-head network evolution for some years may diverge significantly from others, so a longer observation period is of benefit. However 10-year period provided us with some understanding of which effects to look at. For the estimation of SAOM, a computer program called SIENA (Simulation Investigation for Empirical Network Analysis) and its R package RSiena were applied. SAOM models computed within these programs are commonly called SIENA models. The manual for RSiena contains a lot of necessary information for SIENA modeling in R (Ripley et al., 2011).

4. COLLECTED DATA OVERVIEW

The data used for the study include information on tennis matches played among male (ATP) and female (WTA) professional tennis players. The data were freely available online at Kaggle datasets repository Sackmann (2022) and Hakeem (2022), for ATP and WTA respectively and they were analyzed in other researches such as Candila and Palazzo (2020); Gollub (2021); Khder and Fujo (2022); Yue et al. (2022).

Results for the men's ATP tour are recorded from 2001 to 2012, while for the women's WTA tour results and historical betting odds are available from 2007 to 2019. Among the competitions, we excluded Federation Cup in ATP and Davis Cup in WTA.

The datasets contain information about the following: match circumstances (e.g. tournament name, level of tournament, draw size, date, type of surface, round et cetera), match results (final score, length in minutes, number of aces, first serves in, break points saved et cetera) and players' information (name, age, hand, seeding, ranking et cetera).

From the raw data provided in the initial dataset several characteristics of matches were calculated for further analysis. For exploratory analysis, we compared each player's characteristics for their respective year on tour. For social network modeling we took these characteristics for a calendar year.

These characteristics, described briefly in Appendix A, are:

- number of tough sets won against all number of tough sets played (*tsw_tsp*).
- number of easy sets lost against all number of easy sets played (*esl_esp*),
- number of matches won against higher-ranked opponents out of all matches against higher-ranked opponents (*wahr)*,
- number of matches lost against lower-ranked opponents out of all matches against lower-ranked opponents *(lalr)*.

Before the modeling, an exploratory analysis was conducted. In total there are 32870 and 32053 matches in datasets, respectively for ATP and WTA. Then, 1640 men unique players and 1528 unique women players were involved. Among them, 463 men players and 570 women players have ever won a match.

In Table 1 the descriptive statistics of demographic characteristics of players in ATP and WTA are shown. Among players, the average player's height is 185.3 cm and 173.9 cm respectively for ATP and WTA winners, while for losers the average height is 184.9 cm for men and 173.2 for women. Both winners' and losers' age in ATP and WTA have approximately the same range.

The differences in mean for age and height between men and females, and between losers and winners have been tested, and the null hypothesis is always

Table 1: Descriptive statistics of demographic characteristics of players in ATP and WTA

ATP				
Variable	Winner/Loser	mean	s.d.	range=max - min
Age	winner	25.51	3.64	23.9
	loser	25.72	3.63	29.3
Height	winner	185.3	6.52	40
	loser	184.89	6.61	40
WTA				
Age	winner	24.64	4.04	30.8
	loser	24.43	4.26	32.8
Height	winner	173.87	6.64	37
	loser	173.17	6.63	37

rejected (all p-values are less than the smallest $\alpha = 0.001$). Thus, the age and height between winners and losers and with respect to gender are statistically significant.

In Figures 1-4, a comparison between the distribution of age and height in ATP and WTA for winners and losers is shown.

Looking at the age of winner and loser, we can see that in WTA there are a larger number of outliers, meaning that women play tennis for a longer time than men. Moreover, for winners both distributions of ATP and WTA are positively skewed and have a similar variability, while for losers in ATP the distribution of age seems to be negatively skewed, and for WTA it seems almost symmetric (Figures 1 and 2).

Some differences can be observed in winners and losers' height for ATP and WTA (Figures 3-4). In fact, for both winners and losers the distribution of men's height moves towards higher values, while women's height has a distribution around lower values. Moreover, for winners it seems there is a symmetric behaviour, while for losers a negative skewness in ATP is opposed to a positive skewness in WTA.

Furthermore, the match length, measured in minutes, is longer in ATP, which is due to the fact that at some tournaments men are playing 5-set matches, and the variability is higher in WTA (Figure 5).

Among players, there were significantly more right-handed players than left-

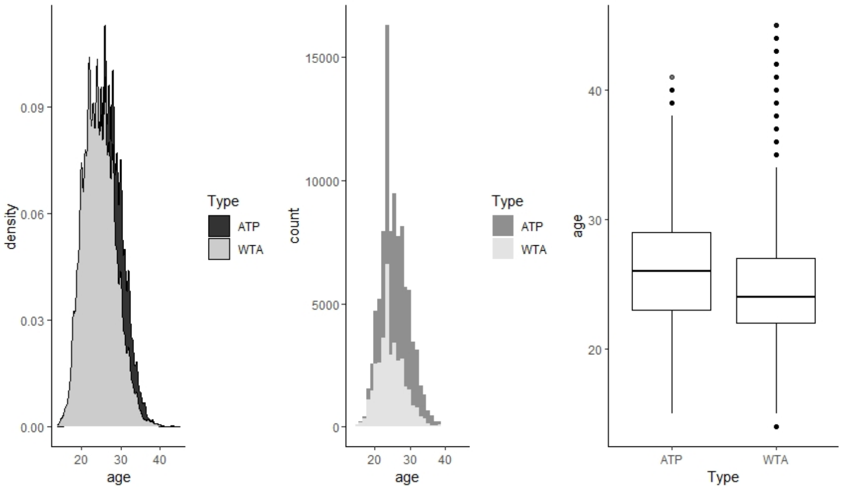


Figure 1: Histogram, density plot and boxplot of age for winners in ATP and WTA

handed ones for both winners and losers (right-hand winner: 87.97% for men and 89.93% for women; right-hand loser 86.25% for men and 88.36% for women) (Figures 6a and 6b).

5. NETWORK ANALYTIC RESULTS AND DISCUSSION

For our analysis we chose three years as the length of study period for a wave with three snapshots taken at the end of each year and a lag of a year between the starting point of two waves. E.g. a wave can start on 1st January 2001 and end on 31st December 2003 with three snapshots taken on 31st December 2001, 31 December 2002, and 31 December 2003. The first network represents head-to-head record at the end of the first year based on all match records for this year, the second network represents head-to-head record at the end of the second year based on all match records for the first two years et cetera. Summary of RSiena models was extracted over 10 waves for each tour. In Table 2 we indicate the number of times each effect was significant out of ten waves and its sign (if significant). Please refer to Appendix A for Name of effect deciphering and details. Ego or Alter column indicates if the effect was evaluated from ego or alter perspective. Function type stands for one of the network evaluation functions (tie emerging, maintaining, dissolving). The example RSiena output for years 2008-2010 on ATP tour for the model with alter effects and creation function is in Table 3. The Table presents estimates (log-probability ratios for the estimated parameter to provide a

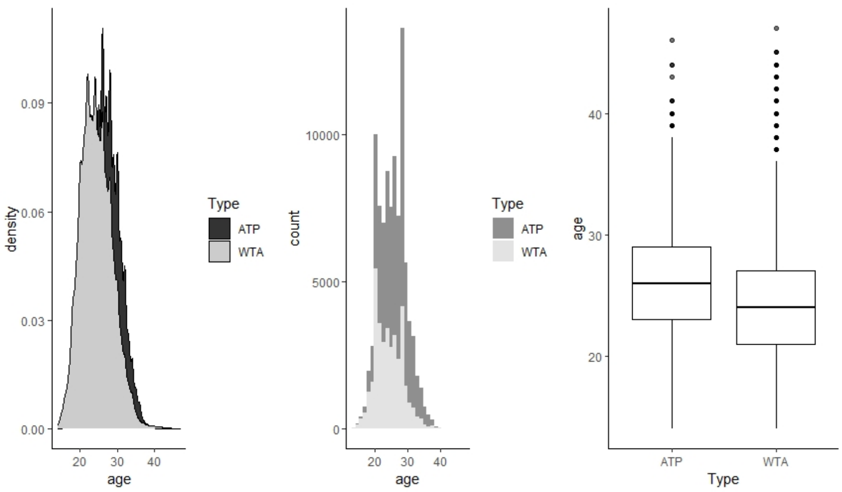


Figure 2: Histogram, density plot and boxplot of age for losers in ATP and WTA

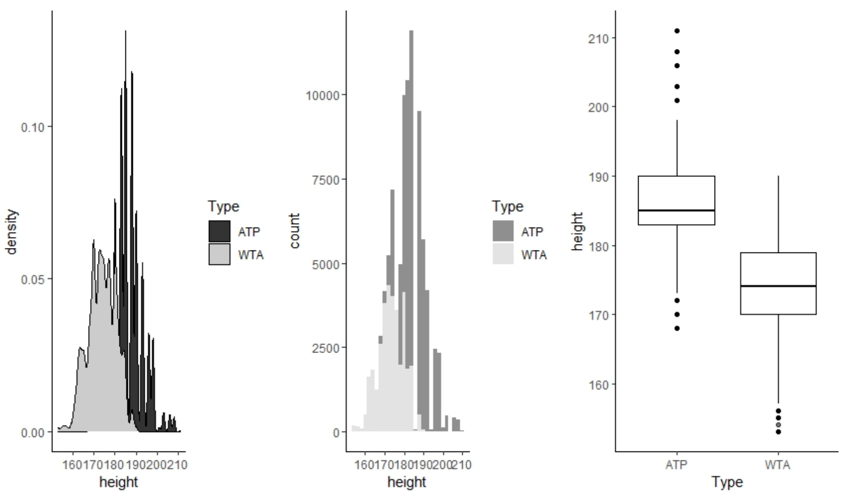


Figure 3: Histogram, density plot and boxplot of height for winners in ATP and WTA

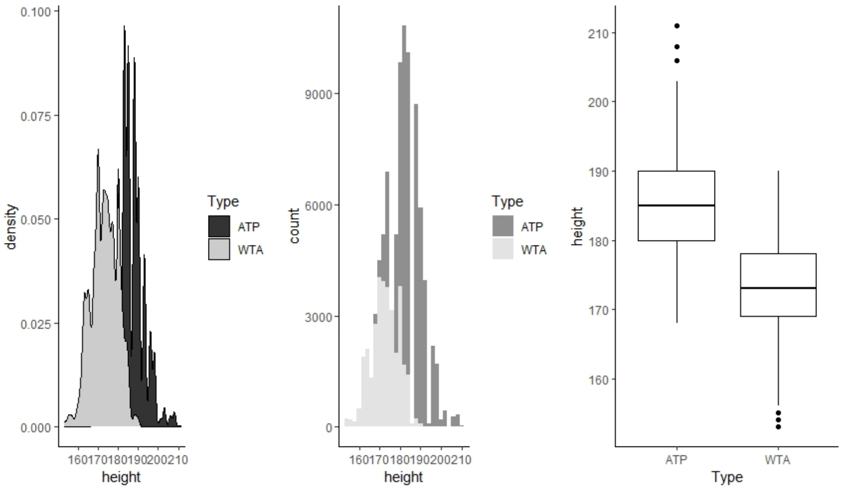


Figure 4: Histogram, density plot and boxplot of height for losers in ATP and WTA

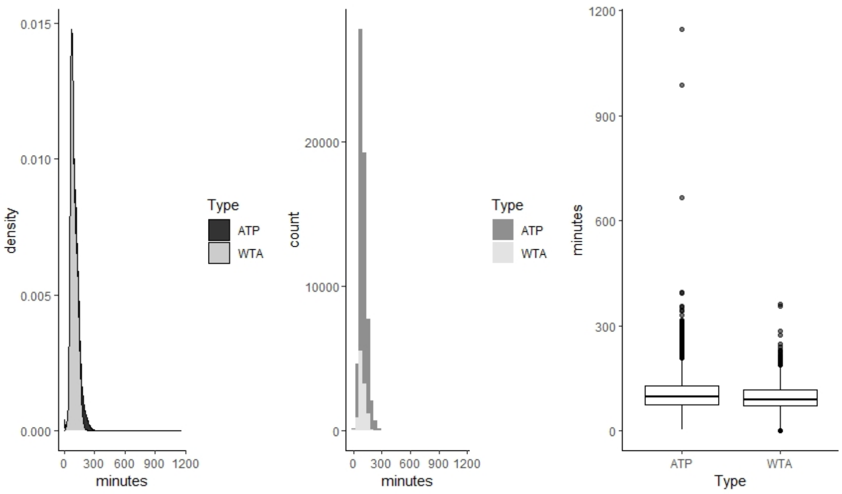
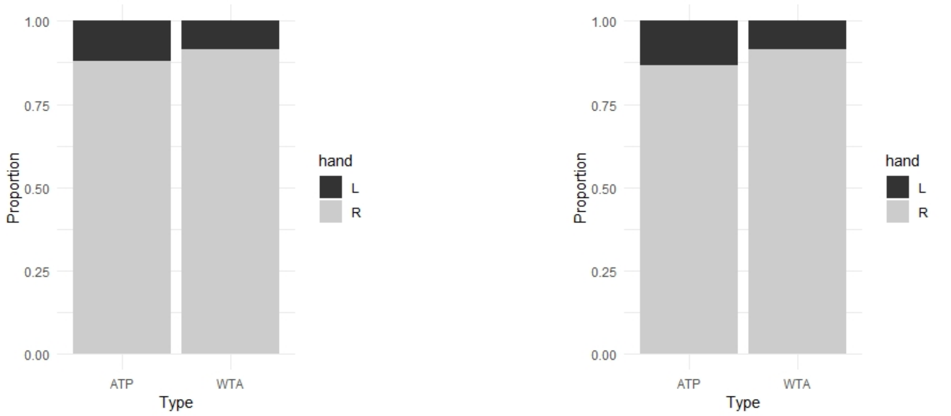


Figure 5: Histogram, density plot and boxplot of match length in minutes in ATP and WTA



(a) Winner hands

(b) Loser hand

Figure 6: Plot of players hands in ATP and WTA

change to the network) and standard errors for network and behavior dynamics, convergence t-ratios (or t-statistics for deviations from targets, which is an indicator of model convergence) and overall maximum convergence ratio (which is another indicator of convergence for the whole model). In Figure 7 we provided an example of the network presentation of wave 10 of male competition (ATP). It can be observed that the network is very dense, and the calculated average degree is slightly over 26. On average, players are linked with 26 opponents, i.e. players established on average 26 head-to-head relations with their opponents between 2010 and 2012 (both years included). The highest out degree in this network (i.e. the highest number of positive head-to-head), is obtained by David Ferrer by achieving a positive score against 108 opponents. He also faced a relatively high in-degree number (i.e. negative head-to-head). His score was negative against 22 opponents. The "big three", Federer, Nadal and Djokovic, are following closely. Federer with the second highest outgoing degree (out-degree: 92; in degree: 8), Nadal fourth (86;8), and Djokovic sixth (83;9).

A summary of RSiena models was extracted over 10 waves for each tour. For simplicity, in Table 2 we indicate the number of times each effect was significant out of ten waves and its sign (if significant). The RSiena output for years 2008-2010 on ATP tour for the model with alter effects and creation function is in Table 3.

For the WTA network effect of weights by respective head-to-head transitivity is either non-significant or of neglectable magnitude (less than 0.1). This

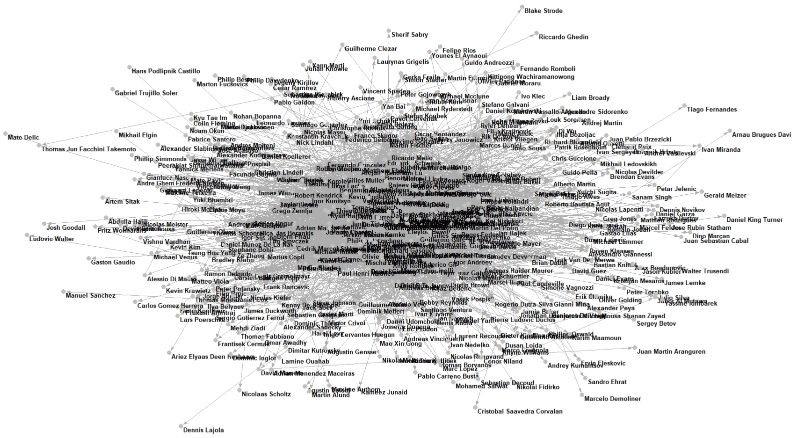


Figure 7: Network presentation of the wave 10

Table 2: Summary of models

Name of effect	Ego or Alter	Function type	ATP	WTA
Transitive closure	-	Evaluation	1 (out of 6, +)	4 (1 +/ 1-)
3-actor cycle	-	Evaluation	5 (out of 6, +)	10 (+)
tsw_tsp	Ego	Creation	N/A	10 (+)
tsw_tsp	Alter	Creation	10 (+)	10 (+)
tsw_tsp	Ego	Endowment	10 (-)	10 (+)
tsw_tsp	Alter	Endowment	8 (-)	10 (+)
esl_esp	Ego	Creation	N/A	8 (-)
esl_esp	Alter	Creation	10 (-)	9 (+)
esl_esp	Ego	Endowment	10 (+)	4 (+)
esl_esp	Alter	Endowment	10 (+)	8 (+)
wahr	Ego	Creation	N/A	4 (-)
wahr	Alter	Creation	6 (+)	0
wahr	Ego	Endowment	6 (-)	0
wahr	Alter	Endowment	3 (-)	0
lalr	Ego	Creation	N/A	8 (4 +/ 4 -)
lalr	Alter	Creation	8 (-)	6 (+)
lalr	Ego	Endowment	7 (+)	0
lalr	Alter	Endowment	7 (+)	0

means that the chance of player A to win against player C and build a positive head-to-head if player A has a positive head-to-head against player B and player B has a positive head-to-head against player C, is close to guessing; thus we should reject hypothesis 1 for the WTA.

For the ATP the same effect was significant only in one wave with four waves not converging to produce results. However, the magnitude of the effect was very high (170.6665), which indicates a high transitivity tendency of the network. Since in other years, the transitivity effect was not significant, we should reject Hypotheses 1 for the ATP as well.

Additional evidence against Hypothesis 1 is a significant tendency of the networks to build a 3-node cycle. Though not strong for the WTA tour and rather strong for the ATP tour. Since the cycle is not a hierarchical structure, it is impossible to rank players within the cycle and cast doubts on the possibility of "fairer" ranking attempts (Aparício et al., 2016; Dingle et al., 2012; Motegi and Masuda, 2012; Spanias and Knottenbelt, 2013) as well as great predicting power of rankings (Boulier and Stekler, 1999; Del Corral and Prieto-Rodriguez, 2010).

Hypothesis 2 is partially supported by different strengths and parameters for ATP and WTA. Winning tough sets which we regard as the ability to thrive under pressure is a significant effect for both the ATP and the WTA players. A positive parameter implies the tendency that players with higher winning tough sets percentage increase their positive head-to-head towards other players more rapidly than average, which is the case for the WTA tour. Also, the magnitude of this parameter is high (between 7.2622 and 48.2832 for different waves). This result is in line with the indication that both men and women perform worse under the pressure of advanced stages of tournaments with women being more prone to unforced errors at crucial junctures of matches (Paserman, 2007).

Controversial to this result, a high percentage of winning tough sets also contributes to higher incoming ties (or negative head-to-head for a player) which we observe for both ATP and WTA players. However magnitude of the effect is small ($0.3842 - 1.3247$ for ATP and $0.2013 - 1.4888$ for WTA). A potential explanation would be the strong possibility to build positive head-to-head due to the ability to thrive on pressure and the weak possibility to build negative head-to-head due to letting the set to be tough because of neglectance. Thus hypothesis 2a is partially confirmed for ATP and WTA players.

Interestingly, winning tough sets decreases the chance for ATP players to lose head-to-head advantage (dissolve positive head-to-head and get negative). On the opposite, for the WTA players such chance increases, that corresponds with higher confidence ability for male athletes (Nicholls et al., 2019). Our results correspond with the finding that if male player wins a tough tie-break, he has a 60% chance of winning the next set (Page and Coates, 2017). However, Page and Coates (2017) no effect was found for women.

The ability to win against higher-ranked opponents turned out to be irrelevant for WTA players. In some waves, it even decreases the chance to build positive head-to-head, however in less than 50% waves. Winning against higher-ranked players slightly increases the chance to get negative head-to-head for male players and decreases the chance to averse existing negative head-to-head. However it also greatly decreases the chance of averse positive head-to-head as well. Thus, we have to reject Hypothesis 2C.

Being prone to lose against lower-ranked players controversially increases the chance to build positive head-to-head for female players in some waves. However, this could be explained by the fact that the chance of losing against lower-ranked players is generally higher for higher-ranked players with them being still able to build many positive head-to-heads despite of losing a lot against lower-ranked players. For other waves, this effect decreases the chance to build a positive head-to-head, which was anticipated. For female players losing against lower-ranked players is irrelevant for existing head-to-heads, while for male players losing against lower-ranked players will slightly decrease the chance of getting negative head-to-head (magnitude of the parameter between -0.2982 and -0.9993), strongly increase the chance of averting positive head-to-head (magnitude of the parameter between 5.3690 and 51.6434) and less strongly increase the chance of averting negative head-to-head (magnitude of the parameter between (2.4922 and 11.9606).

Losing easy sets percentage is crucial for male players. On one hand, a high percentage of easy sets lost counterintuitively decreases the chances of negative head-to-head for the player. On the other hand, a high percentage of easy sets lost increases the chance of reversing head-to-head from positive to balanced or zero, which is expected. It also increases the chance of reversing head-to-head from negative to balanced or positive. For female players losing easy sets percentage decrease the chance of building positive head-to-head and increase the chance of building negative head-to-head, which is different to ATP. The influence of losing easy sets percentage on reversing head-to-head is the same as for ATP players though significant in fewer waves. This is in line with findings by De Paola and Scoppa (2017) that women are more discouraged when facing the pressure of

Table 3: RSiena output for years 2008-2010 on ATP tour for model with alter effects and creation function

Name of effect	estimates	SE	conv t-ratios
Network Dynamics			
1. rate constant (period 1)	4.2885***	(0.1117)	0.0645
2. rate constant (period 2)	3.9953***	(0.0864)	0.0379
3. creat tsw_tsp alter	1.3247***	(0.0770)	0.0748
4. creat esl_esp alter	-1.1097***	(0.0700)	0.0072
5. creat wahr alter	0.2467	(0.3205)	0.0400
6. creat lalr alter	-0.2982	(0.1562)	-0.1074
Behavior Dynamics			
7. rate ranking behaviour (period 1)	0.8083***	(0.0889)	-0.0540
8. rate ranking behaviour (period 2)	1.0115***	(0.1331)	-0.0314
Overall maximum convergence ratio:	0.1610		
Total of 949 iteration steps.			
*** - significant at the 0.001 level.			

falling behind in sets and receiving negative feedback.

6. CONCLUSION

Our study concentrates on the in-match psychological traits of players and the network effect of head-to-head networks. For both ATP and WTA tours in-match psychological traits of players are crucial for their ability to get and keep positive records against other players. For female athletes, the most crucial statistic is winning tough sets, while for male players – not losing easy sets. Also ranking matters more for male players while winning against higher-ranked players or losing against lower-ranked players do not provide much information on a female's potential to get a positive record against other players. Furthermore, a tendency of head-to-head networks to cyclic structures is revealed.

There exist some practical implications. On the one hand, players should understand that psychological traits can be sometimes at least as important as physical condition. They will be able to build a tennis match strategy taking into account the psychological characteristics of their opponents. Tennis coaches should be aware of differences in psychological traits between females and males that were identified in this study. Moreover, those coaches who will be able to quantify explored properties in psychological traits will be able to advise their players to make better decisions on the court. On the other hand, results should interesting also for sports fans and journalists who cover tennis sport very closely.

This work has some limitations. First of all, we were limited by the dataset. Recently, a lot more information regarding tennis matches is being collected and therefore more options to develop hypotheses with related characteristics will be tested in the future. Secondly, working with RSiena on a relatively large network requires a lot of computer power. Consequently, we were to a great extent restricted by the number of applicable model effects. Thirdly, in the current version of RSiena there is no option to work with weighted networks.

To the authors' best knowledge, this study represents the first attempt to use RSiena in the field of sports and we believe that this study can be a good starting point for further work. Besides including other model effects, additional players' characteristics can be used. It would be interesting to compare differences in network dynamics between ATP and WTA regarding the surface (clay, grass, hard court) or tournament type (Grand Slams versus others). Considering the popularity of sports in general and the availability of data, there are plenty of opportunities to carry out similar research in other sports. In particular, individual sports with match-related characteristics and many matches played among players such as table tennis, badminton, snooker and similar can benefit a lot from this kind of study.

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A. Appendix: A description of variables used in SIENA model

As described in Section 1, we considered some characteristics for estimating SIENA models. Here is their brief description.

- *number of tough sets won against all number of tough sets played - tsw_tsp*

  We transfer from match to set statistics because it's the lowest available level of analysis as a unit. Moreover, a match can consist of a different number of sets. Also, a match can consist of sets of different toughness. Averaging match toughness will result in losing variability information.

  A set should be considered tough if a loser has won at least 5 games in the set. We should note that if both players won 6 games each, in most tournaments a tie-breaker is played, which requires maximum concentration.

- *number of easy sets lost against all number of easy sets played - esl_esp*

  A set should be considered easy if the loser has won no more than 2 games in the set. As opposed to tough sets played statistics, the easy-sets statistic should be rather regarded as a ratio of how more often a player is on the winning side of easy sets than on the losing. The more a player is losing easy sets, the less will win he demonstrates.

- *number of matches won against higher-ranked opponents out of all matches against higher-ranked opponents - wahr*

  Usually, a higher-ranked opponent is considered a favorite to win the match. The fact that a higher-ranked player has lost a match can be explained by one of the following:

  - A higher-ranked opponent performed badly in the match.
  - A lower-ranked opponent performed outstanding in the match.

  Both players could be unaware of the abilities of the opponent due to the fact that they have never played before.

  When calculating these characteristics we've used raw ranking and not ranking cohorts in RSIENA model. In this respect, we should note that players of approximately the same strength might have close ranking and if one's ranking is higher, it doesn't provide much useful information. Still, we consider winning against the higher-ranked opponent as a strong will to win.

- *number of matches lost against lower-ranked opponents out of all matches against lower-ranked opponents - lalr*

  This is the opposite of winning against higher-ranked opponents.

  We should mention that the higher is the person in the ranking, the less opportunity he has to play against higher-ranked opponents and the more opportunity he has to play (and lose) against lower-ranked ones, which can potentially affect statistics.