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Abstract

Understanding the interest of sports fans in professional tennis has valuable operational and marketing implications for tournament organisers, marketeers, player sponsors and the media. In sports, professional tennis in particular, the player effect on social media user engagement is still elusive. Using data from the 2019 Australian Open grand slam period, the authors examine Adler's (1985) theoretical construct in the context of sports and social media. A social listening tool is used to probe more than 2 million posts and comments mentioning elite male and female tennis players on four major social media channels: Twitter, Facebook, Instagram and YouTube, over the grand slam period. It is shown that the effect of professional tennis players on social media user engagement extends beyond their talent. A selection of players had a strong positive impact on prompting social media activity, even after accounting for factors related to their performance, the tournament rounds in which they were featured and the opponents against whom they played. Furthermore, the connection between social media research and sports economics is considered by examining the relationship between a player's effects on social media engagement and her/his differential influence on demand for tickets at the Australian Tennis Open. The authors further discuss how the social media star influence can be used, in combination with other quantitative measures, to optimise tennis tournament scheduling, determine player appearance fees and lift participation in the sport.

1. Introduction

Social media has transformed the way consumers engage with businesses and brands. In addition to boosting their visibility on the web and expanding their reach among internet users, social media has become a reliable source for capturing (formal and informal) consumer feedback and the public reaction to web content and core products of these businesses and brands (Gu & Ye, 2014). As such, social media has become extremely popular as a marketing communication medium (Yadav & Rahman, 2017). The focus extends beyond quantifying conversion or referral rates as the key measures for success, to further understanding the broader behaviour of consumers on social channels. For instance, aside from *shopping* online, consumers can profoundly engage with brands on social media with the potential to influence a large portion of the public opinion (Gu & Ye, 2014). Recent figures from the Centre of Marketing Research of the University of Massachusetts (Barnes, Mazzola, & Killeen, 2019) show that, only one out of America's 500 largest corporations, namely the "Fortune 500", was not using not actively using social media to connect with its audience. This comes as no surprise given the enormous user base that is currently active on social media platforms. Facebook, the social media behemoth, presents the perfect example with its 2.49 billion monthly active user-base reported in the fourth quarter of 2019, generating USD20.7 billion in revenue entirely from advertising over that period (Facebook, 2019).

The strategic (use and) presence on social media has been shown to have a big impact on the popularity and marketing goals of businesses/brands. For instance, in year 2019, the earnings of the top 10 highest paid YouTubers (two of which are under the age of 10) hit $162 M (Forbes, 2019). Given its huge potential in transforming the marketing and branding sectors, the study of social media has attracted researchers and practitioners, from a wide range of fields, who are interested in deepening their understanding of consumer activity and preference behaviour on social channels. For instance, the role of social media has been investigated in relation to predicting and enriching advertising activities, enhancing customer relationship management and creating stronger association between consumers and brands (Alalwan, Rana, Dwivedi, & Algharabat, 2017). Several quantitative measures (Hearn & Schoenhoff, 2016;

Rao, Spasojevic, & Dsouza, 2015; Kred Influence Measurement, 2011), many of which have underlying proprietary algorithms, have been developed to highlight (to corporate partners, stakeholders and the public) the level of engagement and popularity associated with a brand on social media platforms. Social media research has found positive associations between consumer motivations to engage with luxury brands on social media, and the propensity to use these brands (Jahn et al., 2012). Interestingly, the level of user engagement on social media further appears to predict brand loyalty (Jahn et al., 2012; Liu at al., 2019).

The sport industry—because of its high profile, visibility and emotional engagement of fans, athletes, industry professionals and customers—offers an excellent platform to investigate the potential impact of social media on the success of its actors. Filo, Lock, and Karg (2015) shed light on the value of social media in the business of sport, particularly from a brand perspective. As sports organisations become more competitive and consumers become more demanding for higher-quality content and entertainment, the pressure is mounting on them to focus on a consumer-centred strategy that delivers world-class events to its patrons. Consequently, an understanding of the superstardom phenomenon, by identifying how talent and success relate to each other, has become a fundamental practice in sports, and its (business) implications are manifold. Firstly, stardom can be one of the main drivers for motivating fans to physically attend sporting events, contributing to higher revenue for sports organisations through ticket purchases (Chmait, Robertson, Westerbeek, Eime, Sellitto & Reid, 2019). As we discuss later, understanding the stardom phenomenon could present tournament organisers with an objective approach to determining the appearance money (Lynch & Zax, 2000; Scully, 2002) that is offered to leading players (to encourage them) to participate in tournaments.

Besides growing the appetite for demand for tournament attendance and television consumption, leading players act as ambassadors for their sport. Thus, superstars play a role in incentivising new individuals to discover and/or become (more) active in playing the sport. The latter also has financial benefits as it can lead to higher revenue from increased demand on facilities and larger membership registrations or subscriptions. Moreover, some observations associate increased sales of merchandise and other sports paraphernalia to leading athletes promoting such products in marketing campaigns (Williams, 2018). Last but not least, leading players also tend to earn considerably more from endorsements than prizemoney (Badenhausen, 2019), so meaning that being able to identify emerging players that could be highly influential on social media presents a commercial opportunity for player management.

2. Literature Review

2.1. Theories of superstardom

The superstardom phenomenon is frequently discussed in the context of Rosen's (1981) and Adler's (1985) theories debating the role of talent and popularity in explaining the emergence of superstars and their market value. Rosen (1981) distils stardom down to talent, whereas Adler (1985) argues that stardom emerges among equally talented individuals and emphasizes fame and popularity as the attributes shifting the needle. In other words, Rosen links the phenomenon of superstardom to talent, and proposes that "small differences in talent become magnified in large earnings differences" (Rosen, 1981, p. 846), whereas Adler (1985) stresses on the importance of positive network externalities and claims that stardom arises among equally talented *artists*.

The theories of Rosen (1981) and Adler (1985) have been examined in a range of domains as, for example, the contemporary visual art market (Candela, Castellani, Pattitoni, & Di Lascio, 2016), music album sales (Filimon, López-Sintas, & Padrós-Reig, 2011) and sports (Franck & Nüesch, 2012; Lucifora & Simmons, 2003), to name a few. Traditionally, the literature has prioritised talent (i.e., the quality of a team or a player) to be a major factor/motive underlying fans' consumption of sport (Funk, Filo, Beaton, & Pritchard, 2009; Hansen & Gauthier, 1989; Kunkel, Doyle, & Berlin, 2017; Shilbury, Westerbeek, Quick, Funk, & Karg, 2014). Consequently, the *value* of athletes has been occasionally equated to their performance on the court (e.g., Gilsdorf & Sukhatme, 2008; Radicchi, 2011) or their professional rankings. In tennis, player *quality* is frequently estimated by the player's world ATP rankings (Association of Tennis Professionals, 2019) or her/his Elo ratings (Elo, 1978).

While strong player talent is usually associated with higher popularity of the sport, other (non-performance related) attributes of fame and popularity also strongly influence audience preferences in soccer (Franck & Nüesch, 2012; Lucifora & Simmons, 2003). This suggests that Adler's 1985 theory pertains to the domain of sports. For instance, the distribution of incomes of soccer players could not be merely explained by their talent (Lucifora & Simmons, 2003). In similar vein, in baseball, the surge in the income of batters appeared to be more proportional to the batter's experience rather than their efficiency or output (Blass, 1992). Recent studies that investigated the *value* of tennis players showed that the star status can have significant positive effects on consumer demand for both stadium attendance (ticket sales) and television consumption, above and beyond factors related to the player success and admission or subscription prices (Chmait et al., 2019; Konjer, Meier, & Wedeking, 2017; Lewis & Yoon, 2016). Whether through the lens of live sports consumption on television or in stadium, the case for evaluating the star status has proven to be a very insightful activity, bearing significant implications for the management and operation of the sports under investigation.

To the knowledge of the authors, it is still unclear if Rosen's (1981)'s or Adler (1985)'s proposition is more applicable to the star status in the context of sports (professional tennis in particular) and social media. Perhaps the most relevant work around this subject matter is that of Kiefer and Scharfenkamp (2012; 2018) on the impact of physical attractiveness on the popularity of female tennis players on social media. The study shows that attractiveness might have a positive influence on the popularity of tennis players on social media. Nevertheless, for a number of reasons discussed hereafter, more evidence is required to recognise which of Rosen's (1981) and Adler's (1985) theories best applies in the context of tennis and social media[1]. Firstly, only one social channel, namely Facebook, was contemplated for measuring social media popularity (while other prevalent channels also exist). Moreover, the study only uses the number of

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[1] In contrast, Kiefer and Scharfenkamp (2012; 2018) provide a comparatively much richer and more comprehensive analysis of these theories in the context of *online* media.

Facebook followers as the sole measure of player popularity. The number of followers, as we describe in detail in Section 2.2, was demonstrated for not being the appropriate measure of popularity on social media. Furthermore, the study does not control for player performance rakings/ratings but rather estimates player talent from their prizemoney. The latter can be a biased measure since prizemoney in tennis strongly depends on (i) the type, status and number of tournaments in which the players were featured so far in their careers (i.e., how active a player has been), and (ii) the level or performance of the opponents they have played against in those tournament; for instance, tennis grand slams reward players for simply making it into the slam, and then incrementally reward the players for each round they proceed into. In addition, the study is limited to (top ranked) female tennis players and no insight is given on men's tennis. Last but not least, as the discussed in (Kiefer & Scharfenkamp, 2018), "the evaluations of the tennis player's physical attractiveness might be biased" since only German university students were asked for their evaluation. As a result, such evaluations are subjective and therefore it is not possible to control for differences in perception of physical attractiveness between evaluators from different regions/countries. To that end, examining superstardom and its constituents in sports (i.e. tennis) and social media can offer a valuable new perspective which is what we set out to do in the study.

Thus far, besides the aforementioned open research question, there are also missing links between the star status research in social media and sport economics. For instance, it is not clear if, and to what extent, tennis stars' social media engagement relates to their influence on demand for tournament event attendance. The research and business opportunity lies in combining star power value with business profit maximisation. The need for comprehending the role of athletes on social media engagement is amplified as the next generation of sport consumers are now favouring digital and social media platforms over broadcast television as their primary source of sport consumption (Media Chain, 2019; Facebook IQ, 2019). Moreover, evaluating the influence of stars on the engagement level of social media users can help inform (and optimise) business decisions related to tennis tournament scheduling, determining player appearance fees in non-grand slam tournaments and adjusting admission prices, amongst other things. Therefore, one of the aims of this study is to investigate whether individual tennis superstars have a significant impact on prompting higher user engagement on social media.

2.2. Measuring influence on social media

Social media platforms are typically used in different ways and for different purposes (Penni, 2017; Ahmed et al., 2018). Deciding on which metrics to be used for measuring user engagement on social media requires careful consideration. For instance, some social metrics fall short of capturing a substantial category and volume of online activity that is (pro-actively, rather than re-actively) initiated by fans on social media platforms. Such pro-active engagement (i.e., social media *mentions* that are posted by the fans themselves, rather than simple reactions to existing posts) associated with sports stars can arguably be considered as a form of super-engagement. Cha, Haddadi, Benevenuto & Gummadi (2010) have empirically demonstrated that measures based on the number of social media followers on Twitter reveal little about the influence of the account holder. This is in accordance with the million follower fallacy discussed by Avnit (2009) who revealed that a large portion of social media users follow (other) individuals simply for *etiquette* purposes, often without reading the content posted by these individuals. Interestingly, Cha et al. (2010) reveal that it is much more influential to have an active fan base that mentions (and shares the content of) a user on social media platforms than merely having a large number of followers. This suggests that the emphasis is transitioning from a passive social media user engagement to an active one. With that in mind, we refer to *social media engagement* associated with a tennis player as "the total number of, original and shared, posts or comments mentioning that player on social media platforms". To explore which of Adler's or Rosen's propositions is more applicable in our context, we will test whether engagement on social media (as defined in the previous sentence) can be sufficiently explained by player talent (his/her performance ratings).

A large proportion of the research investigating sport and social media has been reported in Filo, Lock, and Karg (2015) highlighting its applications in sports management and marketing where the authors categorise social media research into: strategic, operational, and user-focused. The strategic research investigates how social media facilitates brands' reach and communication with users as well as building relationships and promoting brand activities. Operational research focuses on how to leverage the types of content shared by brands whereas the user-focussed research analyses social media based on the demographics (and other attributes) and explores motives for engaging with different types of social media content. Recent research on social media in sports also examined its use as consumers simultaneously watch live sporting telecasts, a phenomenon referred to as the second screen consumer engagement (Phonthanukitithaworn, & Sellitto, 2017). The authors show that the behavioural intention of sport consumers using social media as a second screen is linked with the increased use of the social platforms to make purchases, make recommendations and learn more about sponsors. This highlights the potential of social media in ultimately driving higher revenue for sports organisations and help them attract corporate partners. Hwang & Lim (2015) also explored second screen activity and identified "convenience, excitement, and information" as the three main engagement motives for the use of social TV during a sporting event. Furthermore, Mudrick et al. (2016) showed that there is positive relationship between the use of social media for sports expression and strong team/athlete identification, and demonstrated that social media platforms are efficient tools for keeping fans behaviourally active with sport consumption.

Tiago et al. (2016) analysed the social media profiles and content created by six famous athletes, namely: Cristiano Ronaldo, Lionel Messi, Tom Brady, Aaron Rodgers, LeBron James, and Kevin Durant. The authors compared athlete popularity on Twitter and Facebook by aggregating the number of likes, comments and shares they gathered on their posts. The authors then proposed a strategic model for a more effective social media use in regard to leveraging brands and players' roles in social media, and to boost engagement with their audience. Similarly, Pegoraro (2010)'s study compared the use of Twitter by different athletes and the type of content they shared on this social media platform. They reported that athletes predominantly discuss their personal lives and respond to fans' queries through Twitter, and show evidence that some athletes, such as Serena Williams, purposely used social media for marketing purposes. A survey by E-Poll and Nielsen media research (Van Riper, 2011) assessed the likeability and awareness of selected sports celebrities showing that National Association for Stock Car Auto Racing (NASCAR) drivers were becoming more popular and influential among sports fans in the United States compared to other sports professionals in the year 2010. However, recent figures show that NASCAR has been declining in popularity as a result of not accommodating to the changing audience preferences and dynamics (Gold, 2019). In tennis, Kiefer and Scharfenkamp (2012; 2018) have shown that the *attractiveness* of female tennis players has a positive impact on the number of their Facebook followers (and other online non-social media), yet prizemoney appears to be a more accurate predictor of their popularity.

2.3. The conventional outlook on athlete influence

Many studies have examined the relationship between famous athletes (or teams) and the related consumption of the sports of soccer (Allan & Roy, 2008; Brandes, Franck, & Nüesch, 2008; González-Gámez & Picazo-Tadeo, 2010; Jewell, 2017; Lawson, Sheehan, & Stephenson, 2008; LeFeuvre, Stephenson, & Walcott, 2013; Madalozzo & Berber Villar, 2009; Parrish, 2013), baseball (Gitter & Rhoads, 2010; Gitter & Rhoads, 2011; Lewis & Yoon, 2016; Nesbit & King-Adzima, 2012; Ormiston, 2014), basketball (Berri, Schmidt, & Brook, 2004; Burdekin & Idson, 1991; Jane, 2016) and other sports (Borland & MacDonald, 2003; Coates & Humphreys, 2012; Kunkel, Doyle, & Berlin, 2017; Lenten, 2012; Paton & Cooke, 2005). This work has consistently shown that sports celebrities have positive effects on consumer demand; an effect that exceeds that which is attributable to their performance and other factors such as admission prices (Lewis & Yoon, 2016) to the sport event. For instance, Jewell (2017) discussed how the signing of David Beckham increased attendance figures at the Major League Soccer matches in the USA. Likewise, the stardom effect was observed in connection to demand for National Basketball Association stadium attendance (Jane, 2016) and television consumption (Hausman & Leonard, 1997). Player status has also been linked to an increase in attendance at one-day cricket games (Paton & Cooke, 2005) and can be a primary driver for attendance in Major League Baseball (Ormiston, 2014). More recently, Chmait et al. (2019) showed the effect of tennis stars on attendance figures following an examination of ticket sales at the Australian Open Grand Slam. These researchers observed that the star status influenced ticket sales beyond the performance of the players, the admission prices to the grand slam sessions, and other match schedule details in which the players were featured. In similar vein, demand for live broadcast of tennis matches in Germany (Konjer, Meier, & Wedeking, 2017, Appendix Table A1) also suggests the presence of loyalty effects for individual (domestic) tennis stars.

Engaging fans is of utmost importance to professional sport organisations as a substantial share of their revenue relies on the consumer demand for, and satisfaction with, their products. As it has become clear so far, fans can engage in the sport in multiple ways, whether by playing sport, physically attending an event, watching matches on live television or digital media or interacting with their favourite sport and players on social media (platforms). With the ever-increasing competition between sport organisations and their efforts to increase the value of their broadcasting rights, understanding the influence of players on core products delivered by such sport organisations (from live events to television and social media) can be highly lucrative for sport managers, marketeers and the media in general. While the literature offers a comprehensive overview of the influence of players on both demand for stadium attendance and television consumption, the examination of the social media component remains disproportionally low.

Equating the player effect on live broadcast to event attendance or social media can be controversial. For instance, Mongeon and Winfree (2012) and Cox (2018) showed that important differences can exist between the determinants of economic demand for television audience and gate attendance. It therefore seems logical that this might also apply to social media where engagement is not constrained (no seating capacities), it is typically free of charge and it is not restricted to the time or content of broadcast of the sport event (in contrast to live television). Consequently, evidence is required before extrapolating a player's effect on live broadcast or demand for tickets to her/his effect on social media fan engagement. In the next sections, we systematically explore the influence of tennis stars on engaging social media users (as previously defined in this paper) in a similar fashion to the studies performed around demand for tickets and television consumption.

3. Methodology

3.1. Conceptual Model

The economic theories of superstars presented and discussed by Rosen (1981) and Adler (1985) mark our starting line of investigation in this paper. The fundamental aspects of stardom are examined in the context of professional tennis and influence on social media. The overarching goal is to understand how differences in player talent and player status can generate differences in (prompting) social media user engagement. As discussed in previous sections, such player effects can bear enormous implications on the sustained success of the athlete and their (social media) endorsement earnings, among other things.

Previous research in social media marketing conceptualised customer engagement as a multi-dimensional construct consisting of cognitive, emotional, and behavioural building blocks (Liu, Shin, & Burns, 2019). Nevertheless, only behavioural metrics of engagement tend to be captured in such studies due the limited ability to adequately measure cognitive and/or emotional aspects underlying customer engagement on social channels. Indeed, Liu et al. (2019) analysed the effect of brands on consumer engagement on social media and showed that all 13 studies evaluated, exclusively measured behavioural characteristics of customer engagement despite some advocating for a multi-dimensional conceptualisation of consumer engagement. Likewise, in this study, we only measure behavioural features of consumer engagement on social media platforms. Further details about the captured behavioural features are provided in the sections to follow. A high-level conceptual model summarising (the scope of) our research is presented in Figure 1. Beyond player talent and status, the fundamental aspects of the stardom component, other variables can impact (the influence of players on) social media user engagement. In professional tennis, these correspond to tournament and match related factors (synchronous to when the observations are collected). We discuss these variables in more detail in our model definition.

The player stardom effects have been previously investigated in the context of ticket sales and demand for stadium attendance in professional tennis (Chmait et al., 2019). Hence, a logical extension of our analysis is to identify connections that might exist between the effect of individual professional tennis players on (i) social media and (ii) stadium attendance. To achieve that, we rank the players under study according to how strongly they can impact (i) social media user engagement and (ii) demand for tournament attendance. We then analyse the correlations between the player ranks as we elaborate later.

Insert Figure1

The considerations discussed in the paper so far lead us to propose and examine the following hypotheses:

- **Hypothesis 1**: Professional tennis players can have positive effects on the engagement of fans on social media platforms beyond their performance.
- **Hypothesis 2**: Players with higher influence on demand for event attendance will also have higher influence on prompting social media engagement.

3.2. Data collection framework

Social media mentions of a total of 84 professional (male and female) tennis players were monitored, worldwide, throughout the 18-day period around and during the 2019 Australian Open grand slam. This includes tracking of social mentions from the two days prior to the start of tournament until the two days following its completion. This was the only data available at the time of writing, and it was restricted to the above time-frame due to the strong seasonality present as part of the nature of this problem. A social listening tool, namely SalesForce Social Studio (SalesForce, 2015), was set up to probe posts and comments comprising player mentions on four leading social media channels: Twitter, Facebook[2], Instagram and YouTube, and major discussion forums and blogs. All of the players under study were participants in the 2019 Australian Open.

[2] Due to recent privacy terms and regulations with respect to the use of Facebook data, user posts that are set private from the public are not picked up by our social listening tool.

Data was also collected about each player's matches in the 2019 Australian Open during the grand slam period. We compiled—a conceivably exhaustive set of—keyword groups to identify all possible mentions/references associated with each player on social media platforms. In other words, a dictionary of all player-related keywords has been created to map the terms (or nicknames) associated with each individual player.

3.3. Exploratory analysis

The number of mentions of the 84 players during the period under study tallies to 2,084,331 mentions, having a *std. dev.* $\sigma = 9552.5$. A bar chart showing the total number of mentions for each player during the time period under investigation is provided in Figure 2 for all players who have had 5000+ mentions. Note that a mention of a given player is associated with a social media or blog/forum post (in the form of a text message or captioned image), or the retweet or sharing of a post, comprising (at least) one of the keywords associated with that player. For example, a mention of Roger Federer could be a *tweet* of the text: "I enjoyed watching <Federer> play this evening at the Australian Open". Following a keyword analysis of web content linked to the players under study, we have created (hopefully) an exhaustive set of keywords that could refer to each player including (official and non-official) hashtags, relevant acronyms or nicknames associated with these players. For instance, the word <Federer> in the tweet text above could be replaced by any other term that Roger Federer is known by.

Insert Figure 2

Figure 2 shows that Rafael Nadal had the highest number of mentions followed by the women's singles champion Naomi Osaka and then Roger Federer. We observe a heavy-tailed distribution of mentions dominated by a few superstars. Interestingly, Pareto's principle (Pareto, 1964), also known as the 80–20 rule, seems to elegantly describe the given distribution of social mentions whereby 81% of social media mentions are linked with 20% of the *population* (players). As they stand, these summary statistics can be very valuable to marketeers and large sports event sponsors who pursue partnerships with popular players and seek their endorsement. Nevertheless, these social mention summaries fall short of explaining the genuine player effect on engaging users on social media. In this paper, we design a regression model to understand the individual-player fixed effects on stimulating fan post activity on social media platforms. Before we give the full specifications of our model design, we provide a descriptive summary of our data and discuss the range of variables taken into consideration whilst testing our hypotheses.

3.4. Data variables and summary

The list of variables considered in our analysis is provided in Table 1. Our analysis considers social media post data from all countries and time zones. Naturally, sport fans located in different time zones might post about players at different (dates and) times of day. Despite such differences, we found that fan peak posting activity associated with a player typically coincides with the span of the tournament round in which this player was featured. As a result, we grouped the social mentions associated with a player by round (or stage) of tournament as opposed to doing it on a daily basis (or other shorter timeframes). The outcome variable in our model would therefore correspond to the observations generated by the grouping of each player's social media mentions by tournament round (inclusive of a 48-hour timespan of pre-and post-tournament), and the resulting sample size is one of n = 742 observations.

Insert Table 1

Mentions of a player on social media often appear in the same post alongside mentions of the opposing player. As such, in some instances, the volume of social mentions of a given player is driven by the interest in her/his opposing superstar. To isolate the effect of individual tennis players, we control in our model for both the *Player* and (her/his) *Opponent* variables in each round of the tournament. The identities of the participating players under study are provided in Table 1. To further emphasise the significance of the player influence on prompting social media engagement, we compared the players to a designated base-level or reference player (denoted as "ref." in Table 1). The reference player is chosen from the pool of participants in such a way that his/her total number of (social media) mentions in the first round of the tournament (where all players were featuring) has the minimum absolute square difference relative to the median number of player mentions in that round.

Although more advanced or final rounds of the tennis grand slam tournament tend to be more attractive to patrons who physically attend the tournament (which is typically reflected by the admission prices to these rounds), the influence of the round on social media engagement is not clear. The volume of social mentions associated with a player might be impacted by the event or being eliminated from the tournament. In other words, fans might connect more with players who are still competing in the tournament as opposed to those who have been eliminated. We control for this by introducing the variable *Played* which indicates whether or not a player has been eliminated from the tournament. Furthermore, we control for the variable *Round* to eliminate bias linked to amplified social mentions associated with playing in more advanced or final rounds of the Australian Open. Likewise, different match outcomes, being a *win* or a *loss*, can potentially impact social media activity in different ways. The match result is controlled for by introducing the variable *Loss*.

Finally, we wanted to account for the effect of player quality and her/his performance to understand whether players drive social media engagement beyond their talent. Ideally, we would require historical observations of social media post activity from different years and tournaments to allow us to examine the player effects beyond their talent and performance rankings. As this historical data is not available, it was not fully possible to control for each player's individual performance ranking as such ranking remains static across the period under study. For instance, for non-match observations, we controlled for the variations in social mention volumes that were driven by the individual performance ranking of a player whereas, for match-observations, the average ranking of the featured players in each match was used[3]. This is captured by the variable *Player ATP*. Women's rankings are based on the Women's Tennis Association (WTA) ranking list (https://www.wtatennis.com/rankings). For simplicity, we used the term *Player ATP* to refer to the average player rankings for both males' (ATP) and females' (WTA) rankings. We look at the interaction

[3] Andy Murray's ranking dropped significantly (by 200 ranks) after injury in 2018. To capture the genuine longer term performance of Murray, we used his ATP ranking from before injury.

between *Player ATP* and *Played* given that we are considering observations for players who still feature and/or eliminated from the tournament.

3.5. Formal model specification

As described earlier, our outcome variable corresponds to the volume of social media posts (or shares) mentioning each player, grouped by tournament round. We designed an Ordinary Least Squares (OLS) regression model to investigate the relationship between players and this outcome. In the model specification below, the outcome variable is denoted as *Mentions* and the subscript i refers to a particular observation such that $i = 1, \dots, n = 742$, while ϵ is the error term:

$$\log(Mentions_i) = \alpha + \beta_1 Player + \beta_2 Played + \beta_3 Round\ + \beta_4 Loss + \beta_5 Player\ ATP + \beta_6 Opponent + \epsilon_i$$

We log transform the outcome variable to achieve *normality* in our model. The model passes the Shapiro-Wilk normality test, and the normality assumption is further validated by a graphical assessment of the (residuals) quantile-quantile plot.

The above-specified OLS model allowed us to test the first hypothesis around the effects of players outlined in Section 3.1. Our second objective was to further examine whether players with higher influence on demand for event attendance will also have higher influence on prompting social media engagement (Hypothesis 2). To achieve this, we tested the rank correlations between the point estimates of the player coefficients from our OLS model, and those in Chmait et al. (2019), who examined the player effect of tennis stars on demand for stadium attendance. Chmait et al. (2019) also performed their analysis within the scope of recent Australian Open tournaments. Both Kendall's *tau* (where calculations are based on concordant and discordant rank pairs) and Spearman's *rho* (where calculations are based rank order deviations) rank correlation tests were performed. Of course, only the mutual set of players examined in this study and in Chmait et al. (2019) were tested. First, the point estimates of the mutual players (their effects on social media and independently their effects on ticket sales) were put in order and numbered according to each study. The resulting ranks were then compared and correlations were tested for statistical significance.

4. Results and Discussion

The coefficients from the OLS regression are provided in Table 2. Before analysing the effects of players, we consider how the different independent variables are related to our outcome of interest.

Insert Table 2

4.1. Attributes of social media mentions

Social mentions clearly display variations by *Round*, and depending on whether a player has been eliminated from the tournament or not (*Played*). For instance, more advanced rounds seem to be associated with relatively higher volumes of mentions. This is consistent with fan interest in attending (or watching) tennis matches in the final stages of the tournaments (Chmait et al. 2019; Konjer, Meier, & Wedeking, 2017). Moreover, the positive coefficient for *Played* indicates that social media engagement, in the form of posts and comments, largely corresponds to discussions around the players' matches. In other words, being eliminated from the tournament is associated with a lower volume of social mentions. The match outcome of a player also has a significant relationship with her/his earned mentions. We observe that players who win a match seem to drive higher engagement compared to those who lose.

The investigation of whether player quality/performance helps to explain a player's influence on social media engagement is a novel part of this study. It is frequently tested in the literature by examining Rosen's (1981) vs. Adler's (1985) theory on the emergence of stardom and star income. For instance, Rosen (1981) linked superstardom to performance by proposing that minor fluctuations in talent are amplified in big earnings differences, whereas Adler (1985) stressed fame and popularity, beyond talent, as key features that resulted in stardom emerging among equally talented performers/athletes. From Table 2, we observe that the *Player ATP* ranking has a significant negative relationship with the outcome variable. This is expected since a higher ranking of players (equivalent to a lower numerical rank value) increases the volume of posts associated with these players. The overall picture is that fans discuss or mention more talented players. More specifically, for non-match observations, the coefficients indicate that for every one unit increase in the players' ranking value (less performing players), the volume of social mentions associated with these players decreases by roughly 0.88% whereas the decrease is around 0.22% for match observations (*Played* is True). Although talent has a significant impact on our outcome variable, the effect of players extends beyond the performance element as we will see next.

Given that two players compete in a tennis singles match, it is likely for social media users to mention both contesting players in the same post (e.g., simply discussing a particular match on social media instead of a player). This is accounted for by controlling for the *Opponent* variable. The coefficient for *Opponent* is omitted in the interest of space, noting that coefficients of individual players are very similar under *Player* and *Opponent*. To facilitate the interpretation of the player effect, we plotted the coefficients for each player under study in Figure 3, along with the confidence intervals of our estimates.

Insert Figure 3

4.2. The player effect

Beyond their talent or playing quality, Figure 3 shows that 17 out of the 88 players in our study appear to have had a significant positive impact on the volume of social media mentions around the Australian Open timespan, with Roger Federer topping the list. Serena Williams was the most *engaging* professional female player in the 2019 tournament. The estimates for these 17 players all exceed (at the 95% confidence interval) the base level volume of mentions among the sample expressed in the estimates of our reference player. Interestingly, the gender split is almost evenly split between female and male players (9 and 8 players respectively). World number one at the time, Novak Djokovic, ranks sixth on our list of most influential players on social media post activity. In contrast, popular figures in the media like (arguably) Maria Sharapova were among the top 10 influential players despite having a WTA ranking of 30 at the time. Although several domestic players participated in the 2019 grand slam, only one Australian player, namely Nick Kyrgios, appeared to have had a significant effect, suggesting that social media engagement might be resilient to home bias. However, more research is required to test this hypothesis. It is important to note that the high social media engagement rank for Andy Murray could be attributed to the announcement of (his possible) retirement due to injury after losing his first match at the Australian Open. As a result, more data is required to validate Andy Murray's estimates.

In summary, looking at the resulting player coefficients, our data seems to support Adler's thesis in professional sports (Adler, 1985; Blass, 1992; Franck & Nüesch, 2012; Lucifora & Simmons, 2003, Chmait et al. 2019) indicating that some popular players can indeed be much more influential in the social media sphere than other players that have similar performance rankings or professional history.

4.3. Bridging social media and demand for tickets research

Present research on social media star influence has not been linked to the literature of sport economics, and particularly to the impact of stars on demand for stadium attendance. To the knowledge of the authors, this is a first attempt to bridge the two fields by providing some fundamental insights into how the player effect on demand for ticket sales compares to that of driving social media activity. Rank correlations between the common set of players examined in this study and from Chmait et al. (2019), who investigated the player effects on ticket sales at the Australian Open, are provided in Table 3. Although there is no absolute concordance between the paired samples in the two studies, it is obvious that a strong positive correlation exists. Interestingly, both the top and bottom ranked players in the two studies are identical. Table 3 shows that Spearman's rank correlation between the set of 14 players is strong and positive $\rho = 0.916$, indicating that our observations have fairly concordant pairs, as well as being statistically significant (with a very small p-value < 2.2e-16). This is also the case with Kendall's τ which returns a rank correlation > 0.78 (noting that Kendall's τ values are typically smaller than Spearman's ρ).

Insert Table 3

Overall, our tests show a positive relationship between the influence of star status on demand for attendance (i.e., ticket sales), an important subject in sports economics, and social media user activity. In other words, players with higher influence on demand for event attendance are also likely to have higher influence on social media engagement. There are different ways that sport organisations can benefit from this analysis and finding. We elaborate on the business implications of our work in the next section.

5. Business Implications

Our findings show that beyond their performance ranking there are supplementary stardom effects resulting from the player status in regard to social media engagement, analogous to the conclusions from the literature on demand for attendance in sport (Hausman & Leonard, 1997; Lewis & Yoon, 2016; Ormiston, 2014; Paton & Cooke, 2005, Chmait et al., 2019). Although more talented players commonly attract more fans, our study reveals that the star status in social media extends beyond the quality and career performance of the athlete in agreement with Adler's thesis in professional sport (Adler, 1985; Blass, 1992; Franck & Nüesch, 2012; Lucifora & Simmons, 2003).

In addition to the aforementioned research findings, the outcomes from this study have several business implications that can enrich the way sport organisations manage players, campaigns and tennis tournaments in the future. In the digital sport era, there is the likelihood that consumers will discover the sport of tennis through its professional players who are leading influencers on social media. As a result, famous players may play a key role in incentivising young individuals to commence playing tennis as well as lifting participation rates among existing tennis players, consequently resulting in larger consumer investment of time and money in the sport. Indeed, the practice of nominating players to feature in targeted advertisements and marketing campaigns, based on their (empirically measured) charisma and user appeal on social media, may encourage amateur players to become more active with the sport (both physically and as spectators) and can assist in promoting sales of merchandise and other tennis products (Williams, 2018). A study to quantify the magnitude of these presumed effects of tennis superstars in the marketing campaigns of tennis organisations could follow.

Player-management enterprises can also leverage the research on player social media influencers by identifying and helping less-influential players in strengthening their off-court and social media activities that can develop the player brand value. For those new and upcoming players particularly, our results can be used as part of a framework for the assessment of the (social media, marketability and onsite) *value* of these players in their endeavour towards a professional sport career that entails more than becoming a high performing player on court. With the enormous competition for prizemoney and other performance-related earnings, tennis athletes, beyond their playing excellence, can become more commercially relevant and popular among the public. In light of this, highly influential players on social media may have the potential to generate more revenue off the court (e.g., in endorsements or sponsorship) than from tournament participation. Roger Federer offers a fine example with his $65M earnings from endorsements and appearance fees compared to his tally of $12.2M in prizemoney in recent years (Badenhausen, 2019). With that in mind, our findings reveal that equally talented players (or even those of a lower standard ranking) can indeed be more influential, which emphasises the opportunity for upcoming players to develop their brand value.

Day by day, tournament organisers aim to increase the number of consumers who physically attend their events for this constitutes a substantial source of their income (Clark, 2011). To achieve this goal, organisers of tennis tournaments need to strategically recruit top tennis players who can pull more fans into their stadia. In tennis, appearance money (Lynch & Zax, 2000; Scully, 2002) is the fee that organisers pay for star players to participate in (relatively less prestigious) tournaments, and it is one of the main drivers for attracting popular players to these tournaments especially when these appearance fees can (largely) exceed the standard prizemoney offered. Accordingly, measuring the effect of tennis players on social media activity can be valuable to tournament organisers as it may be one of the factors considered in determining the cost-benefit equation of their appearance.

5.1. Some limitations

The lack of access to historical social listening data did not permit us to expand the scope of our analysis to include a variety of tennis tournaments. The absence of repeated observations from different years of the tournament under study might also limit our interpretation with respect to the impact of the player performance rankings on social media engagement. Although we have pulled data from four leading and large social media platforms and blogs, an inclusion of more platforms may have altered the player estimates. Moreover, posts sourced from the Facebook platform were limited to public postings (due to recent privacy regulations) and may not reflect the private views of fans. Without longitudinal data, it is not clear how the influence of players fluctuates over longer timespans. For instance, some players could be highly popular on social media platforms for short periods of time whereas others could be associated with steady figures related to popularity and engagement for extended periods of time.

6. Conclusion

This study demonstrates the relationship between professional tennis players and social media post activity initiated by tennis fans. We account for a range of attributes that could have impacted the volume of social media posts associated with individual tennis players around the 2019 Australian Open grand slam period. We show that the superstardom effect is present above and beyond professional player talent, in support of Adler's thesis that superstardom emerges among equally talented players. As well as being the first empirical examination of the effects of individual athletes on engaging sports fan on social media, this study is a first step towards bridging the social media and sports economics research tracks by testing the proposition that players with higher influence on demand for event attendance (e.g., tickets sales) will also have higher influence on prompting social media engagement.

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Table 1

List of variables included in the OLS regression model and their descriptions.

Variable		Description
Player/Opponent		
Alex Bolt Alex de Minaur Alex Popyrin Alexander Zverev Andreas Seppi Andy Murray	Aliaksandra Sasnovich Anastasija Sevastova Anett Kontaveit Angelique Kerber Aryna Sabalenka Ashleigh Barty	The Player variable holds the names of the players investigated in our study. As these players compete against each other, this list also holds values for the Opponent variable with the exception for "D. Yastremska" and "A.

Bernard Tomic	Barbora Strycova	Pavlyuchenkova" for which we have no social monitoring data. Male and female opponents who participated in less than three matches (those players associated with less than 3 observations) in the tournament are encoded as "Other-Male" and "Other-Female" respectively. Observations from dates peripheral to the tournament start and end dates, as well as those associated with players beaten out of the tournament (players who lost a match), have the Opponent variable set to "No Opponent". The reference or base-level player is Denis Shapovalov (refer to Section 3.4 for more details about this selection).
Borna Coric	Camila Giorgi	
Daniil Medvedev	Carla Suarez Navarro	
David Goffin	Caroline Garcia	
Denis Shapovalov (ref.)	Caroline Wozniacki	
Diego Schwartzman	Danielle Collins	
Dominic Thiem	Daria Gavrilova	
Fabio Fognini	Daria Kasatkina	
Fernando Verdasco	Dominika Cibulkova	
Frances Tiafoe	Donna Vekic	
Gael Monfils	Elina Svitolina	
Gilles Simon	Elise Mertens	
Grigor Dimitrov	Garbine Muguruza	
Jeremy Chardy	Jelena Ostapenko	
John Isner	Johanna Konta	
John Millman	Julia Goerges	
Jordan Thompson	Karolina Pliskova	
Karen Khachanov	Katerina Siniakova	
Kei Nishikori	Kiki Bertens	
Kevin Anderson	Kimberly Birrell	
Kyle Edmund	Lesia Tsurenko	
Lucas Pouille	Madison Keys	
Marin Cilic	Maria Sharapova	
Marton Fucsovics	Mihaela Buzarnescu	
Matthew Ebden	Naomi Osaka	
Milos Raonic	Petra Kvitova	
Nick Kyrgios	Petra Martic	
Nikoloz Basilashvili	Qiang Wang	
Novak Djokovic	Saisai Zheng	
Pablo Carreno Busta	Sam Stosur	
Rafael Nadal	Serena Williams	
Roberto Bautista Agut	Shuai Zhang	
Roger Federer	Simona Halep	
Stefanos Tsitsipas	Sloane Stephens	
Steve Johnson	Su-Wei Hsieh	
Ajla Tomljanovic	Venus Williams	
Round		
1	Pre-Tour	An integer $\in [0, 8]$ that controls for variations in the propensity to mention players on social media, at different stages/rounds of the Australian Open (AO) tournament. The list shows the (integer) value corresponding to each round (right-side) in order of play. The index is reset to zero further to the end of the tournament (Post-Final).
2	R128 (ref.)	
3	R64	
4	R32	
5	R16	
6	Quarter-final	
7	Semi-final	
8	Final	
0	Post-Final	
Played		Determines if a player was featuring in a given round of the tournament (i.e., has not been eliminated).
No (ref.)		
Yes		
Loss		Indicates whether a player has lost a match in the corresponding round (controls for match outcome).
No (ref.)		
Yes		
Player ATP		Controls for the overall player performance/talent. For non-match observations this corresponds to a player's ATP ranking, while the value for match observations is measured by the average ATP rankings of the featuring players. Note that the top ATP rank (highest rank) corresponds to a value of 1. For simplicity, we also use the term ATP to refer to the women's WTA rankings.

Note: ref. indicates the reference category of the variable.

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Table 2
Coefficients from the OLS regression model output showing the fixed effects of tennis players on social media mentions during the Australian Open 2019 time period.

	Dependent variable:
	Social media mentions
Constant	5.1607*** (0.6358)
Player	
Alex Bolt	-0.1277 (0.5137)
Alex de Minaur	0.4711 (0.4434)
Alex Popyrin	0.0039 (0.5024)
Alexander Zverev	0.8993* (0.4470)
Andreas Seppi	-0.7162 (0.4444)
Andy Murray	2.7342*** (0.4446)
Bernard Tomic	0.8076$^{\cdot}$ (0.4644)
Borna Coric	-0.5593 (0.4451)
Daniil Medvedev	-0.2659 (0.4445)
David Goffin	-0.9093* (0.4544)
Diego Schwartzman	0.1235 (0.4409)
Dominic Thiem	0.3183 (0.4421)
Fabio Fognini	-0.6789 (0.4457)
Fernando Verdasco	-0.7008 (0.4450)
Frances Tiafoe	0.8009$^{\cdot}$ (0.4533)
Gael Monfils	0.4341 (0.4410)
Gilles Simon	-1.5584*** (0.4541)

Grigor Dimitrov	0.4311 (0.4450)
Jeremy Chardy	-1.2834** (0.4457)
John Isner	-0.1524 (0.4421)
John Millman	-0.4774 (0.4448)
Jordan Thompson	-0.4789 (0.4670)
Karen Khachanov	-0.6313 (0.4442)
Kei Nishikori	1.2890** (0.4510)
Kevin Anderson	0.8450$^{.}$ (0.4454)
Kyle Edmund	-0.7593$^{.}$ (0.4414)
Lucas Pouille	0.1610 (0.4465)
Marin Cilic	0.5488 (0.4459)
Marton Fucsovics	-1.3021** (0.4666)
Matthew Ebden	-0.0430 (0.4453)
Milos Raonic	0.4145 (0.4499)
Nick Kyrgios	1.2029** (0.4491)
Nikoloz Basilashvili	-1.1261* (0.4585)
Novak Djokovic	1.8873*** (0.4555)
Pablo Carreno Busta	-0.1763 (0.4412)
Rafael Nadal	2.8713*** (0.4554)
Roberto Bautista Agut	0.4156 (0.4493)
Roger Federer	3.3549*** (0.4449)
Stefanos Tsitsipas	1.3884** (0.4485)
Steve Johnson	-2.0119*** (0.5002)
Ajla Tomljanovic	-1.3596** (0.5237)
Aliaksandra Sasnovich	-0.8870* (0.4461)
Anastasija Sevastova	-0.2554 (0.4479)
Anett Kontaveit	-1.6193*** (0.4560)

Angelique Kerber	1.1858** (0.4479)
Aryna Sabalenka	0.2650 (0.4476)
Ashleigh Barty	0.5151 (0.4506)
Barbora Strycova	0.1443 (0.4425)
Camila Giorgi	-1.1257* (0.4461)
Carla Suarez Navarro	-0.9244* (0.4463)
Caroline Garcia	-0.3680 (0.4469)
Caroline Wozniacki	1.2313** (0.4446)
Danielle Collins	0.5778 (0.4556)
Daria Gavrilova	0.1211 (0.4434)
Daria Kasatkina	-0.0557 (0.4432)
Dominika Cibulkova	-1.6565*** (0.4462)
Donna Vekic	-0.5418 (0.4435)
Elina Svitolina	0.4130 (0.4544)
Elise Mertens	-0.9224* (0.4440)
Garbine Muguruza	0.1908 (0.4478)
Jelena Ostapenko	0.6360 (0.4421)
Johanna Konta	-0.0061 (0.4472)
Julia Goerges	-1.0049* (0.4457)
Karolina Pliskova	0.4430 (0.4609)
Katerina Siniakova	-0.7904$^{\cdot}$ (0.4423)
Kiki Bertens	0.2143 (0.4463)
Kimberly Birrell	-0.0954 (0.5757)
Lesia Tsurenko	-1.1048* (0.4424)
Madison Keys	1.6125*** (0.4489)
Maria Sharapova	1.7798*** (0.4447)
Mihaela Buzarnescu	-0.7636$^{\cdot}$ (0.4420)

Naomi Osaka	2.3125*** (0.4749)
Petra Kvitova	1.7737*** (0.4570)
Petra Martic	-0.6332 (0.4492)
Qiang Wang	-0.9253* (0.4473)
Saisai Zheng	-2.2838*** (0.5350)
Sam Stosur	0.1131 (0.4594)
Serena Williams	2.8408*** (0.4536)
Shuai Zhang	0.4910 (0.4481)
Simona Halep	1.8485*** (0.4475)
Sloane Stephens	0.6560 (0.4478)
Su-Wei Hsieh	-0.3101 (0.4456)
Venus Williams	1.1285* (0.4436)
Played	1.8557*** (0.1422)
Round	0.0491** (0.0161)
Loss	-0.7187*** (0.1776)
Player ATP	-0.0089*** (0.0025)
Played**: **Player ATP	0.0066** (0.0021)
Observations	739
R^2	0.8464
Adjusted R^2	0.8189
Residual Std. Error	0.9244 (df = 626)
F Statistic	30.7948*** (df = 112; 626)
Note:	· p<0.1 *p<0.5; **p<0.01; ***p<0.001 Coefficients for *Opponent* omitted in the interest of space.

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Table 3
Spearman's and Kendall's rank correlations between (the rank orderings of) the common set of players examined in this study and in (Chmait et al., 2019).

Player status rank ordering on demand for attendance and social media engagement

	Influence rank	
Player	*Demand for attendance* (*Chmait et al., 2019; Table 3*)	*Social media engagement* (*Table 3*)
Roger Federer	1	1
Novak Djokovic	2	4
Rafael Nadal	3	2
Nick Kyrgios	4	6
Kei Nishikori	5	5
Andy Murray	6	3
Alexander Zverev	7	7
Gael Monfils	8	10
Bernard Tomic	9	8
Domnic Thiem	10	13
Marin Cilic	11	9
Gigor Dimitrov	12	11
Milos Raonic	13	12
David Goffin	14	14
Spearman's rank correlation $\rho \in [-1,1]$	S = 38, *p*-value = < 2.2e-16 Alternative hypothesis: true $\rho \neq 0$ Sample estimates: $\rho = 0.9164$	
Kendall's rank correlation	T = 81, *p*-value = 1.919e-05	

$\tau \in [-1,1]$	Alternative hypothesis: true $\tau \neq 0$ sample estimates: $\tau = 0.7802$

Figure1

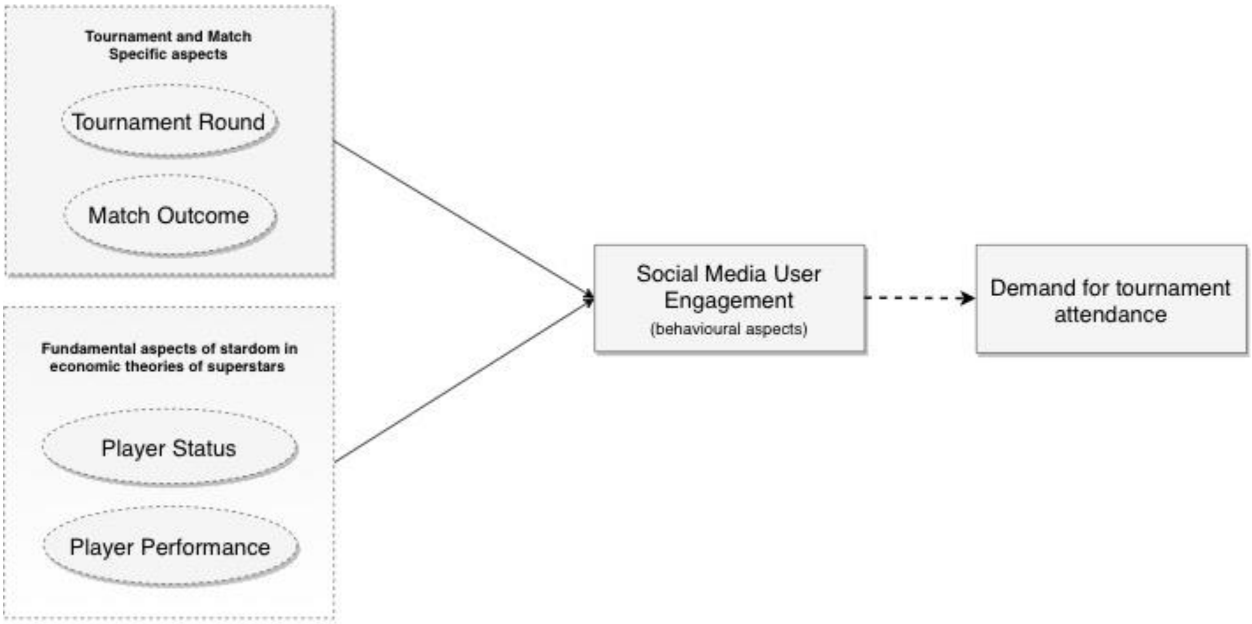

Fig. 1. Proposed high-level conceptual model showing the main components investigated in this research and their relationships with user engagement on social media. The two components consist of (i) aspects underlying superstardom theories and other (ii) tournament specific aspects. The relationship between the superstardom component and social media user engagement is also compared (dotted lines) to how that component has been shown to influence demand for tournament attendance in the existing literature. The conceptual model relates the two hypotheses identified in this research.

Figure2

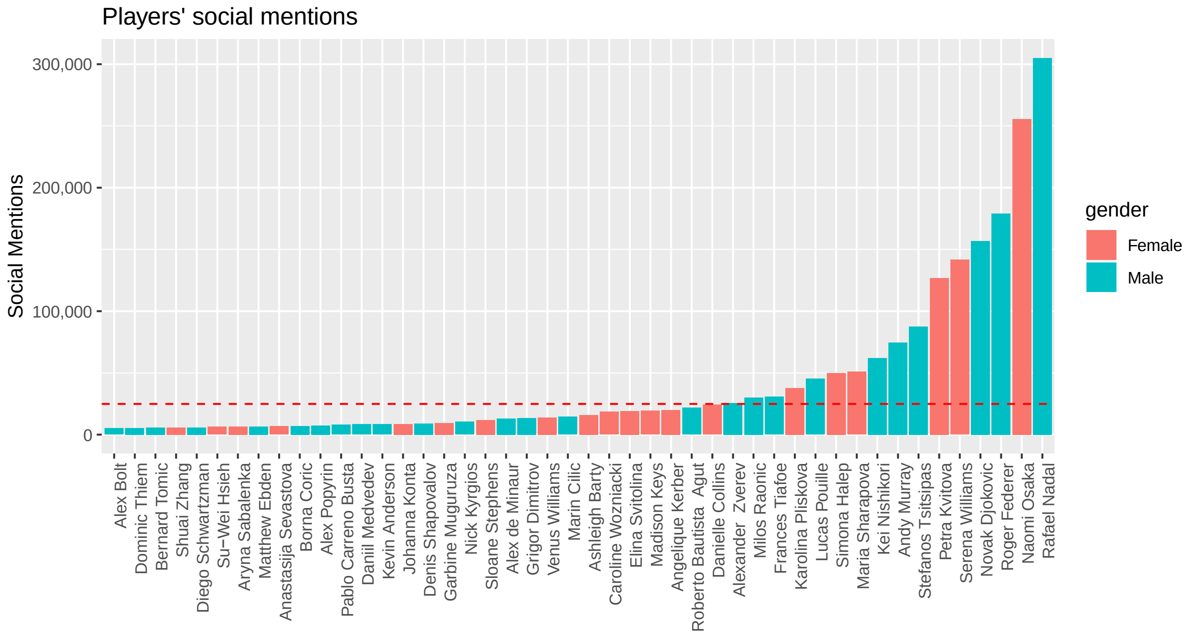

Fig. 2. A bar chart of the total number of mentions associated with players during the time period under study. Only players with 5000 or more social mentions are plotted. The colour identifies the gender of the player while the red dotted line shows the average social media mentions across all (appearing and non-appearing) players.

Figure3

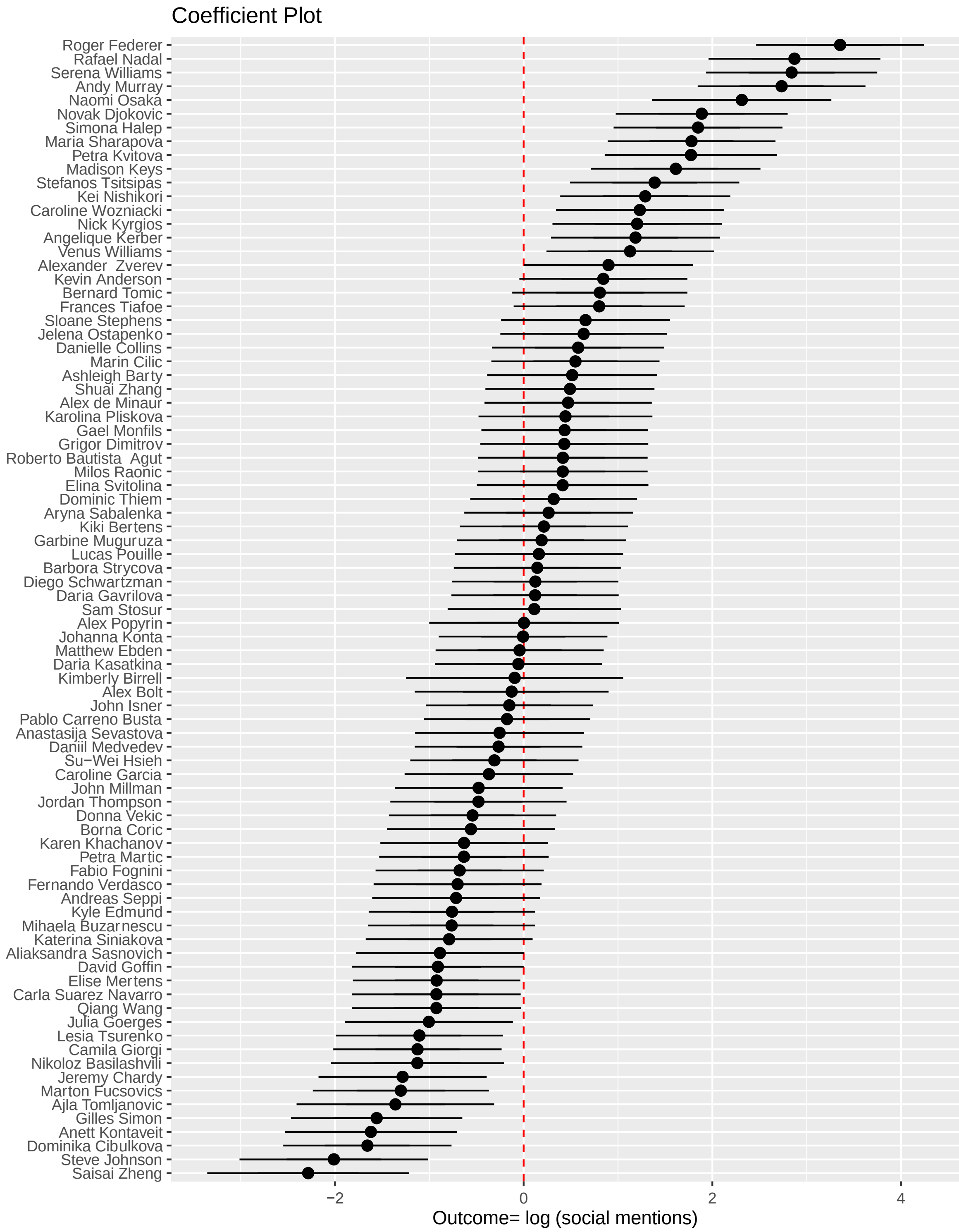

Fig. 3. Coefficient plot from the OLS regression model showing the fixed effects of the players on the (log transformed) outcome variable corresponding to the players' social media mentions, and their 95% confidence intervals.