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Nataliya Bredikhina, Keshav Gupta & Thilo Kunkel

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Superboosting the athlete social media brand: events as an opportunity for follower growth

Nataliya Bredikhina, Keshav Gupta and Thilo Kunkel

Fox School of Business & School of Sport, Tourism and Hospitality Management, Temple University, Philadelphia, PA, USA

ABSTRACT

Research Question: An athletes' social media following is a proxy of their popularity and a key metric for brand monetization. Yet, how a following can be grown strategically remains unclear. This research investigates the effects of newly formed brand networks on athlete follower growth during a non-league event with representative teams. We used the sport brand ecosystem framework and examined athlete-related, event-related, and brand-networking-related factors as determinants of follower growth on Instagram.

Research Methods: We collected longitudinal behavioral data, namely social media following and tagging behavior of athletes in the context of Laver Cup, an elite men's team tennis event. A sociogram was used to visualize brand networking of athletes and the event. The hypotheses were tested using a multiple linear regression with a wild-cluster bootstrap-*SE*.

Results and Findings: Results indicated that the pre-existing size of an athlete's following and brand networking with athletes' and the event's brands through the user tagging function predicted follower growth. This highlights the impact of exposure on social media during an event and the value of brand networking as a brand-building strategy for athletes.

Implications: The findings contribute knowledge on athletes' vertical and horizontal brand relationships. The study uncovers coopetitive relationships between athlete brands and shows that new brand networks, visible through social media user tagging, spur athlete brand growth. To practitioners, this demonstrates that events enable athletes to strengthen their social media brands, which can be amplified through athletes' large pre-existing social media following and strategic collaborations with other athletes.

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Athlete brand; brand architecture; brand relationships; social media; digital marketing

In the era of social media marketing, the number of followers (i.e. a measurable social media fanbase) of an athlete has become a key metric of monetization potential (e.g. Kunkel et al., 2021). Large followings increase brand visibility and help diffuse brand-related information (Church et al., 2021). Relatedly, athletes are encouraged to

CONTACT Nataliya Bredikhina nataliya.bredikhina@temple.edu Fox School of Business & School of Sport, Tourism and Hospitality Management, Temple University, Philadelphia, PA, USA

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strategically grow their social media fanbases to maximize their brand monetizability. However, what strategies drive athletes' follower growth remains largely unexamined.

Participating in a highly publicized event may help athletes increase their social media fanbases. For instance, many United States (U.S.) Olympians and Paralympians have benefitted from the Olympic and Paralympic Winter Games in PyeongChang in 2018 (USOC, 2018). Specifically, snowboarders Chloe Kim and Shaun White saw an increase in social media following by over 800,000 new followers each, and U.S. Paralympians had an average increase by 6.5 percent in following. Although extant research has addressed how athletes' social media brands grow within the sport league brand ecosystem (Su et al., 2020), the understanding of longitudinal changes in athletes' social media brands beyond the league setting, such as during non-league events with representative teams (e.g. the Olympic Games), remains lacking. Further, offering a longitudinal perspective is imperative to understand the temporal influence of brand environment on athletes' social media brand growth.

Athlete brands are elements within a sport brand ecosystem, i.e. a brand environment comprising sport entities that interact and impact one another, including sport organizations and human brands (Kunkel & Biscaia, 2020). Like other brands in the sport brand ecosystem, athlete brands benefit from mutual spillover effects (Kunkel & Biscaia, 2020). For example, a team's popularity impacts the popularity of an athlete joining that team (Su et al., 2020), whereas producing content with fellow teammates can positively impact fan engagement with athletes' brands (Doyle et al., 2020). The interconnected nature of brand relationships suggests that understanding how athletes' social media brands grow during an event requires accounting for sport environment-related and athlete-specific factors. Beyond regular season leagues and schedules, there exist many highly publicized professional, elite amateur, or exhibition events across sports. Events such as the Fédération Internationale de Football Association (FIFA) World Cup in soccer, the Ryder Cup in golf, or the Laver Cup in tennis provide opportunities for athletes to grow their personal brands by leveraging the horizontal and vertical dimensions of the sport brand ecosystem.

This study examines the factors that influence athlete brand growth on social media during a high-profile non-league event with representative teams. As athletes decide whether to participate in events beyond their league schedules, they must negotiate the trade-offs and benefits thereof, including physical load, schedule fit, and personal, monetary, and brand benefits. Our study examines the mechanisms driving athlete social media brand growth during such events, providing insights to event organizers pitching their proposals to athletes as well as athletes seeking to strategically strengthen their brands. We used longitudinal data from athletes competing in the Laver Cup, an elite-level men's tennis event, for our investigation. Our study offers insights into sport consumer behavior on social media and contributes a theoretical understanding of how elements of the event brand ecosystem affect athletes' social media brands.

Literature review

Athlete branding on social media

Social media enables fans to follow and connect with athletes (Doyle et al., 2020; Geurin-Eagleman & Burch, 2016). Successful social media branding provides multiple benefits to athletes, including sponsorship income (Hayes et al., 2020), fan support (Sveinson & Hoeber, 2020), and attractive brand positioning during team transfer negotiations (Doyle et al., 2020). Relatedly, athletes face growing demands to develop their social media personal brands to connect with fans and activate sponsorships (Geurin, 2017). An athlete's number of followers is a proxy for their social media brand popularity and a paramount metric for social media brand monetization (Kunkel et al., 2021; Su et al., 2020).

Prior research has focused predominantly on athletes' social media posting practices or fan responses toward those practices. Through content analyses, scholars investigated athletes' self-representation (e.g. Emmons & Mocarski, 2014; Geurin-Eagleman & Burch, 2016; Li et al., 2021). For instance, research has shown that male and female athletes brand themselves differently, with men creating more athletic and action-oriented content and women highlighting more emotion-laden and brand-focused content (Emmons & Mocarski, 2014; Lebel & Danylchuk, 2012). Scholars have also investigated how female athletes navigate the contradictory demands of femininity and athleticism in their self-presentation, uncovering the complex interplay of multiple identities, functions, and narratives combining front- and back-stage performances (Li et al., 2021; Shreffler et al., 2016; Toffoletti & Thorpe, 2018). Further, content analyses have helped determine patterns in athletes' sponsorship promotions on social media, such as ambush marketing during big sporting events (Geurin & McNary, 2021).

Additionally, scholars have explored consumer responses to content produced by athletes. Geurin-Eagleman and Burch (2016) demonstrated the differences between content types (e.g. posts dedicated to sports, personal life, pop culture) posted by male and female Olympic athletes and compared fan engagement with different types of posts for both genders. Doyle et al. (2020) found that content types and marketing orientation impact engagement with professional athletes' Instagram accounts in the context of Major League Soccer. Further, Su et al. (2020) examined the impacts of the National Football League (NFL) brand environment on athletes' social media followings and showed that athlete-, team-, and league-related factors predict athlete brand growth. However, extant research offers a limited understanding of how to strategically grow an athlete's social media brand following.

In this paper, we respond to Su et al.'s (2020) call to investigate how manageable actions taken by athletes, teams, and leagues can impact athlete social media brand growth, with a particular focus on brand interactions, including tagging of associated accounts within a sport brand ecosystem. We extend knowledge on sport brand ecosystem dynamics in the context of a non-league event featuring representative teams and demonstrate how social media features are instrumental in signaling brand relationships.

Athlete brand within the event brand architecture

Sport brands are interrelated (Kunkel & Biscaia, 2020). The sport brand ecosystem is based on the notion of brand architecture (Aaker & Joachimsthaler, 2000) and has been used to explain brand relationships among sport organizations (Kunkel et al., 2014). Brand architecture is defined by vertical and horizontal brand networks (Keller, 2014). Vertical networks are formed based on complementarity and represent a hierarchy of brands working jointly to create a sport product (Kunkel et al., 2014). Considering the league as a master brand and teams as subbrands, the brand relationship between leagues and teams follows a vertical structure with reciprocal brand impacts, including a spillover of consumer perceptions, attitudes, and behaviors (Kunkel et al., 2013, 2014). Human brands, such as athletes and coaches are part of sport brand architecture as vertical subbrand extensions of teams and clubs (Kunkel & Biscaia, 2020; Williams et al., 2015). For instance, university brands, as master brands, impact social media brands of student-athletes (Kunkel et al., 2021), whereas an athlete's on-field and off-field brand image dimensions influence consumer team perceptions (Kunkel et al., 2019). Further, horizontal brand relationships are based on the commonality between similar brands positioned at the same market level (Keller, 2014). For example, Juventus Football Club's men's and women's teams follow a horizontal brand relationship. Similarly, the relationship between brands of athletes competing in the same sport follows a horizontal structure. The conceptualization of sport brand architecture encompasses diverse brand relationships across sports contexts (Kunkel et al., 2013). Non-league events with representative teams temporarily place athletes in new networks of brands, allowing to empirically examine the impact of horizontal and vertical brand relationships on athletes' social media brands.

We depict our conceptualization of the brand ecosystem of a non-league sporting event with representative teams in Figure 1. Prior research suggests the external brands (the league, sponsors, venue, and host city) are positioned as horizontal extensions of the event brand architecture (e.g. Kunkel & Biscaia, 2020; Sant & Mason, 2015). A sport event that is not affiliated with a league is organized by an event committee and has its own brand. For instance, the FIFA World Cup is not governed by national or regional soccer leagues and has its own brand. In the figure, the inner event brand ecosystem is outlined with a dashed box. The event brand is a master brand relative to other brands within the event brand ecosystem. For instance, prior research established the spill-over effects of the event brand on sponsors (Su & Kunkel, 2021), the host city (Chiu et al., 2019), and participating athletes (Kassing & Sanderson, 2010). Thus, the event brand – positioned at the top of the brand hierarchy – guides the dynamics of marketing activities and brand relationships that emerge during the event.

The representative teams competing in the event comprise the event brand's vertical subbrand extensions. Representative teams usually represent countries, regions, or communities and are the creators of the sport product at the event (Kunkel & Biscaia, 2020). The U.S. Women's National Soccer Team (USWNT) is an example of a representative team consisting of elite players who compete in professional leagues during the regular season and are invited to represent the U.S. in qualification tournaments to contest the right to play at major events, such as the Olympic Games or the FIFA Women's World Cup. Representative teams' brands range from established brands (e.g. the USWNT is recognized by fans and sponsors, has its own website and a multimillion following) to event-only brands (e.g. Team Europe at the Ryder Cup emerges as a brand only during the event).

Subsequently, participating athletes are vertical subbrand extensions of their representative teams. Thus, USWNT's athletes Carli Lloyd and Meagan Rapinoe are subbrand extensions of the team brand. Athletes may engage in brand networks with each other, for instance, through joint social media content production (Doyle et al., 2020). Viewing athletes as subbrand extensions of a team helps theorize horizontal athlete-to-

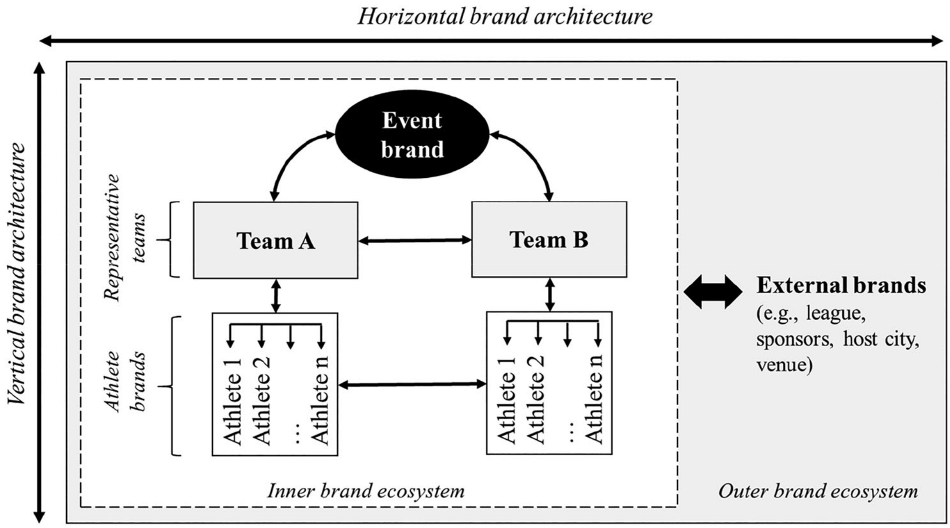

Figure 1. Sport Event Brand Ecosystem.
Note. The figure illustrates a brand ecosystem of a non-league-affiliated sporting event with representative teams. The dashed box bounds the inner event brand ecosystem. The event is a master brand and teams and athletes are vertical brand extensions. The solid-line box signifies the outer brand ecosystem comprised of external horizontal brand extensions of the event brand: the league, commercial brands and sponsors, venue, and host city. Arrows signify brand relationships.

athlete brand relationships (cf. Kunkel & Biscaia, 2020). The framework highlights the interdependent nature of brands at events. For instance, fans following an athlete through an event are by default consumers of the event's product. Event spectators are likewise consumers of the teams and athletes via sports action and drama. Thus, when managing an athlete's brand, it is important to account for the brand network influence.

Factors influencing athletes' follower growth during an event

Athlete brand-related factors

Athletes' social media brand characteristics such as pre-existing follower count and posting patterns may impact their potential brand growth during an event. The number of followers an athlete has is a signal of fans' interest in the athlete (Watanabe et al., 2016). The Matthew effect, suggesting that with time the 'rich' get relatively 'richer' and the 'poor' get relatively 'poorer,' also holds on social media: specifically, pre-existing large followership predisposes the account to gain new followers (Su et al., 2020). Such an effect can be attributable to several factors, including social media algorithms and athlete brand characteristics. Social media algorithms favor content providers with larger followership sizes for their proven ability to attract and retain consumers (Gaenssle & Budzinski, 2021). This makes these accounts more likely to be recommended to future users, improving their visibility (Gaenssle & Budzinski, 2021). Although a large following does not necessarily produce high post engagement or endorsement effectiveness (Brison & Geurin, 2021; De Veirman et al., 2017), prior research indicated consumers view Instagram accounts with more followers as more likable due to their perceived popularity and ascribed opinion leadership (De Veirman et al., 2017). This may incentivize future followers. Further, athletes' social media accounts are an extension of their real-world personas. Relatedly, athletes' unique individual characteristics such as celebrity status (Watanabe et al., 2016), charisma, or attractive brand attributes (Arai et al., 2013) are likely to continue to provide value during the event. This will discriminate the extent of increase in followings between athletes with different levels of prior popularity. Therefore, we hypothesize:

> H1: The number of pre-existing followers of athletes' social media profiles is positively associated with the daily increase in athlete following on social media.

Social media posting patterns have traditionally been considered a relevant measure for assessing social media brands (e.g. Ledbetter & Redd, 2016; Vergeer & Mulder, 2019). The literature provides mixed evidence on the importance of posting frequency for brand success (e.g. Brison & Geurin, 2021; Reynolds et al., 2010). For example, Vergeer and Mulder (2019) reported an insignificant relationship between athletes' tweet frequency and followership size, whereas Liu and Jansen (2013) indicated that when social media influencers (SMIs) on the Chinese microblogging website Weibo posted excessively frequently, that deterred their followers. Still, research on human branding on Instagram, including SMIs and celebrity brands, has suggested high posting frequency is beneficial because it establishes online leadership (Adjei et al., 2012; Gaenssle & Budzinski, 2021; Reynolds et al., 2010). More frequent posts lead to greater information dissemination (Reynolds et al., 2010), whereas social media algorithms favor individuals who post high-volume content, increasing visibility to potential new followers (Gaenssle & Budzinski, 2021). In the context of celebrity branding on Instagram, the frequent posting was found effective in increasing consumer interest and perceived celebrity intimacy and credibility (Ledbetter & Redd, 2016). Further, since fans seek to learn more about athletes behind-the-scenes (Billings et al., 2017), increased posting is likely to be gratified with greater interest and popularity due to perceived access to the athlete. Hence, we hypothesize:

> H2: The frequency of athletes' posting on social media is positively associated with the daily increase in athlete following on social media.

Event-related factors

Athlete brand growth on social media should accelerate during competition days. Industry evidence suggests large sporting events, such as the Olympics Games, impact athlete brands (USOC, 2018). This is likely because master brands are known to affect the development of sub-brands through publicity and brand exposure (Aaker & Joachimsthaler, 2000). Sporting events are effective in generating high interest and sparking conversations in the mainstream media and online spaces. For example, the 2016 Rio Olympic Games gained the reputation of being the 'most social Olympics' as during the event, 227 million users interacted with 1.5 billion posts related to the Games on Facebook alone (Tang & Cooper, 2018). Yet, prior literature also indicates that the publicity and exposure might not be distributed equally among athletes, with star athletes at the top of league standings receiving most attention due to the 'stardom effect' (Watanabe et al., 2016). Event exposure can also amplify attention for athletes who are more favored by local media and fans such as those competing 'at home,' because those athletes can help attract potential consumers. This signals the importance of controlling for possible differences due to athletes' level of success and team affiliation while examining the effects of event-related factors. We provide more details on control variables in the method section. Beyond these effects, in general, considering the marketing potential that the event provides for athletes, we hypothesize:

H3: Competition days are associated with a greater daily increase in athlete following on social media than non-competition days.

Brand networking

Effective business networks are a source of competitive advantage. While brand networking through user tags has garnered scholarly interest in disciplines like marketing (Hsiao et al., 2020) and media and communications (Duffy & Hund, 2015), research on whether user tagging can spur social media brand growth has been lacking. User tagging implies identifying other social media accounts or brands in the user-generated content, for instance on the photograph or in the textual caption, by placing an 'at' sign (@) and listing their username. Exploring the role of user tagging on social media within the athlete branding context represents a relevant future research direction (Su et al., 2020).

A major advantage of brand-brand networking on social media is the ease of signaling brand relationships and reaching the target consumer. Augmented by the visual nature and interconnectedness of social media, tagging makes it easy for the end-user to identify brand relationships. Thus, brand networks between the social media accounts can be signaled through the user tagging function (Duffy & Hund, 2015). When leveraged successfully, brand networking can amplify spillover effects and help reach new audiences (Zhang et al., 2016). Therefore, we expect that being tagged in content by other sports brands increases athletes' social media brand reach.

Within the sport brand architecture, brand networking can occur vertically and horizontally. As a successful firm, a high-quality event master brand is likely to have top human talent, creative, and knowledge resources (Wang et al., 2009), and create high-caliber content on social media. Athletes tagged by the event have their brand mentions appear in engaging, high-quality content. This may particularly benefit star athletes, who represent a lucrative promotional asset for the event (Watanabe et al., 2016) and whom the event is likely to promote more, subsequently reinforcing the Matthew effect on athletes (cf. Su et al., 2020). Further, the target audiences of the event and athletes likely overlap. This applies to both event-to-athlete and athlete-to-athlete interactions. Athletes can use this opportunity to strengthen their social media following by tapping into audiences of other sport brands and strategically signaling their association through tags (Zhang et al., 2016). Lower-ranked athletes may strategically include content with their star teammates to engage their audiences (Doyle et al., 2020). Athletes may also be prone to networking more within the teams due to the spirit of rivalry and because of spending more time with their teammates compared to other athletes, suggesting the importance of controlling for star-level and team affiliation when studying athletes' brand networking (addressed in more detail in the method section). When the followers of a sporting event or an athlete see other athletes tagged in their posts, they become more familiar with the tagged athletes. Furthermore, repeating positive brand information should lead to increased brand popularity and liking (Rindfleisch & Inman, 1998). Therefore, greater visibility and frequency of tagging should lead to greater follower growth for the tagged athletes. Thus, we hypothesize:

> H4: The daily number of times that athletes are tagged on social media posts created by the event is positively associated with the daily increase in athlete following on social media.

> H5: The daily number of times that athletes are tagged on social media posts created by other athletes is positively associated with the daily increase in athlete following on social media.

Method

Research context

In the current study, we examine the determinants of athletes' social media brand growth during a non-league sporting event with representative teams. We studied athletes' follower growth on Instagram, which is considered the top platform for branding (Robinson, 2020). The study was conducted in the context of the Laver Cup, an international, elite-level professional tennis event that took place in Geneva (Switzerland) on September 20-22, 2019, featuring three days of competition. The annual event is conducted in a team format, featuring two representative teams: Team Europe comprising athletes from European countries, and Team World comprising athletes from non-European countries. The Laver Cup is an invitation-based competition, where some of the invitations are earned by players based on ranking, and others are distributed at the discretion of the captain coaches, selected by the event organizers. Each team has a roster of seven players (Laver Cup, 2021).

Following the sport brand ecosystem framework (Kunkel & Biscaia, 2020), the brands of the Laver Cup event, teams, and athletes form vertical and horizontal networks. The event is a master brand with a reputation as an elite-level competition, based on the caliber of participants over the years (e.g. Roger Federer, Rafael Nadal, and Novak Djokovic), global portfolio of leading broadcast platforms (e.g. Eurosport, SuperSport, and ESPN International), reputable sponsors (e.g. Rolex, Mercedes, and UPS), and a worldwide audience. The brands of teams and participating athletes are the event's vertical sub-brand extensions. All participating athletes and the event brand had active accounts on Instagram. Full rosters including alternates were announced five days before the event, allowing us to begin to capture the metrics of athlete following and social media activity before the event start date. The newly formed team environment predisposed athletes to vertical and horizontal brand networking through user tagging and allowed us to gauge the impacts of brand networks on individual athletes' followings, which justified choosing a team event as a context.

Data collection and variables

Data for the study were prepared in two stages. First, we collected data from the athletes' and the event's Instagram accounts. Data collection began five days before the event, continued through the three days of the event, and was completed five days after the event. Daily, we recorded the number of athletes' followers. We also daily collected the number of times that an athlete or the event tagged other participating athletes. Collecting the metrics in the early morning, local time (3 AM GMT+2), allowed to account for the changes occurring by the end of the day, several hours after the games were over and content related to the event was posted by athletes' and the event's accounts.

Second, we organized the dataset for regression in a Microsoft Excel spreadsheet. The collection of metrics for 14 athletes over 13 days resulted in 182 observations. We calculated the absolute daily growth in followers by subtracting from the number of followers on a given day the number of followers on a previous day. Given the uncontrollable nature of on-field performance, we did not operationalize athletes' performance during the event since our exploration focuses on branding-related factors that are of theoretical interest and can be managed by practitioners. Further, fans may evaluate athletes' performance during the event differently. While some fans may associate an athlete's performance with objective measures (e.g. the outcome of the game), others may evaluate it based on subjective factors (e.g. an athlete's style of play; Arai et al., 2013). This makes it challenging to measure the impact of performance on athlete following. The remaining explanatory variables included the daily number of times that athletes were tagged by the event account, the daily number of times that athletes were tagged by other athletes, and the daily number of posts that athletes made. Additionally, we dummy-coded the days of competition (Competition day = 1; Non-competition day = 0).

Control Variables. A range of factors can influence an athlete's social media brand growth during the event. Representative teams' characteristics may differ, differentially influencing athletes' follower growth. For instance, the presence of star players on the team can create spillovers of attention to lesser-known players (Watanabe et al., 2016), whereas teams' popularity among local media and their fans' geographic location and access to live broadcast time can also differ. This can affect branding outcomes and lead to common sources of variance for athletes on the same team. Therefore, we controlled for athletes' team affiliation (Team Europe = 1, Team World = 0). Further, considering that the athletes' overall level of success and stardom may be an important factor in attracting media attention and social media following (cf. Su et al., 2020), we controlled for the athletes' official ATP Tour singles ranking during the week of the event (i.e. September 16, 2019; ATP Tour, 2019).

Based on the abbreviations in Table 1, we apply the following equation as our function for estimating Instagram follower growth for athlete i on day t to test the hypotheses:

$$\begin{aligned} DELTA_{it} &= \beta_0 + \beta_1(FOLLOWERS)_{it} + \beta_2(ATHLETEPOSTS)_{it} \\ &+ \beta_3(COMPETITIONDAYS)_{it} + \beta_4(TAGSBYEVENT)_{it} + \beta_5(TAGSBYATHLETES)_{it} \\ &+ \beta_6(TEAM)_{it} + \beta_7(RANKING)_{it} + e_{it} \end{aligned}$$

Analysis

We utilized R 3.6.1 for regression analysis and ran a multiple linear regression to test *Hypotheses 1-5*. To ensure the absence of multicollinearity between the predictors, we

Table 1. List of Variables with Units of Measurement and Abbreviations

Variable	Unit of measurement	Abbreviation
Dependent variable		
Daily increase in the number of followers	Individual users	DELTA
Predictors		
The number of followers of athlete's profile recorded on a given day	Individual users	FOLLOWERS
Daily number of posts created by the athlete	Post	ATHLETE POSTS
Competition day	Yes = 1; No = 0	COMPETITION DAYS
Daily number of posts made by Laver Cup' where athlete was tagged	Post	TAGS BY EVENT
Daily number of posts made by other athletes where athlete was tagged	Post	TAGS BY ATHLETES
Control		
Team	Team Europe = 1; Team World = 0	TEAM
Player ranking	Position in the ATP Tour ranking	RANKING

examined inter-item correlations (Franke, 2010) and variance inflation factors (VIFs; Hair et al., 2005). Since homogeneity of variance of error terms is an important assumption for an Ordinary Least Squares model, diagnostic tests for homogeneity of variance were conducted. The results of the Breusch–Godfrey test for serial correlation (Breusch, 1978; Godfrey, 1978) indicated that error terms in the model exhibited clustered heteroskedasticity (Astivia & Zumbo, 2019), likely resulting from a hierarchical data structure with temporal, individual, and team-level sources of variance. For instance, at the athlete level, information corresponding to one athlete (e.g. Roger Federer) could exhibit unique patterns different from other athletes (e.g. Rafael Nadal). Similarly, data collected on a given day could exhibit patterns different from other days. Although researchers generally address clustered heteroskedasticity by employing the cluster-robust standard errors approach (CRSE; White, 1980), it has limitations, including biased standard error estimates when a small number of clusters (five to 30) is analyzed and an assumption of one-way clustering with no account for multi-way interrelations (Cameron et al., 2008). While treating each player as a cluster, we sought to address the small number of clusters (14) as well as the temporal and team-level sources of variance. Hence, we utilized a bootstrap-based approach for inference with clustered errors, executing the wild-cluster bootstrap-*SE* (Cameron et al., 2008) with 5,000 iterations to test the hypotheses.

Results

Descriptive statistics and plots

Descriptive statistics revealed that all athletes' followings grew during the data collection period. An overview of athletes' follower growth is presented in Table 2. On average, each athlete gained 1,827 new followers daily. Descriptive statistics are presented in Table 3. Figures 2 and 3 visualize the daily growth rate estimated as a percentage change compared to the previous day for athletes on Team Europe and Team World, respectively.

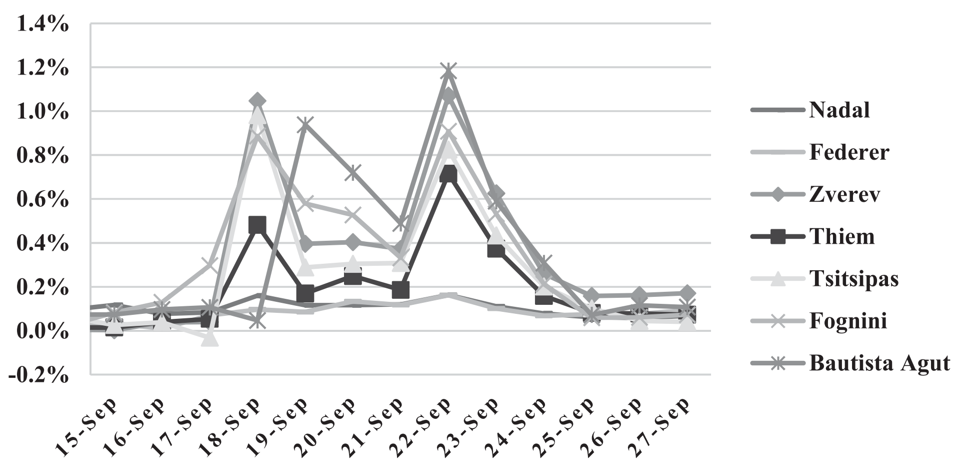

Figure 2. Daily Rate of Change in Athlete Following: Team Europe. *Note*. The figure illustrates a daily follower growth rate during data collection estimated as a percentage change in comparison to the previous day for athletes on Team Europe.

Table 2. Athletes' Follower Growth Overview

	Nadal	Federer	Zverev	Thiem	Tsitsipas	Fognini	Bautista Agut	Isner	Raonic	Shapovalov	Kyrgios	Sock	Fritz	Thompson
9/27/2019	5,409	6,438	1,500	611	277	372	72	108	7	364	759	124	137	22
9/26/2019	4,649	5,290	1,424	654	313	309	77	−40	32	154	1,799	160	156	14
9/25/2019	4,862	5,166	1,387	679	699	299	48	83	−17	200	713	1,055	239	26
9/24/2019	6,271	4,659	2,270	1,321	1,392	1,079	205	83	25	178	1,123	599	401	135
9/23/2019	8,853	6,898	5,444	3,109	2,987	2,691	390	281	−4	282	819	279	693	68
9/22/2019*	12,995	11,083	9,207	5,909	5,625	4,549	774	931	443	672	1,994	916	2,801	157
9/21/2019*	9,529	8,005	3,193	1,532	2,094	1,657	318	667	149	544	1,529	508	664	174
9/20/2019*	9,238	9,112	3,442	2,046	2,065	2,616	465	284	118	995	1,025	853	656	94
9/19/2019	9,218	5,814	3,365	1,394	1,948	2,860	600	292	49	389	812	293	350	107
9/18/2019	12,665	6,588	8,806	3,939	6,575	4,339	30	566	147	432	603	579	988	202
9/17/2019	6,631	4,799	329	440	−214	1,449	68	17	61	100	1,056	138	221	121
9/16/2019	6,105	630	319	318	258	630	62	17	17	105	670	127	166	0
9/15/2019	9,249	2,293	21	118	174	400	47	15	−129	100	620	140	68	−7
Total Δ	**105,674**	**76,775**	**40,707**	**22,070**	**24,193**	**23,250**	**3,156**	**3,304**	**898**	**4,515**	**13,522**	**5,771**	**7,540**	**1,113**
Competition days Δ	10,587	9,400	5,281	3,162	3,261	2,941	519	627	237	737	1,516	759	1,374	142
Non-competition days Δ	7,391	4,858	2,487	1,258	1,441	1,443	160	142	19	230	897	349	342	69
Following on September 15	7,922,612	6,807,400	840,438	816,054	669,100	487,159	63,804	185,732	372,509	331,371	1,269,285	196,687	83,419	14,290

Note. * = competition days. Δ = change in followers.

Table 3. Descriptive Statistics

Variable	*M*	*SD*
DELTA (Daily increase of followers)	1,827	2,778
FOLLOWERS	1,444,684	2,475,238
ATHLETE POSTS	0.54	0.832
TAGS BY EVENT	1.29	1.999
TAGS BY ATHLETES	1.36	2.281
RANKING	19.4	14.89
	Frequency	**%**
COMPETITION DAYS	42	23.1
TEAM	91	50

Note. *M* = mean, *SD* = standard deviation. The frequency and percentage for COMPETITION DAYS and TEAM variables were estimated as the ratio of relevant observations to all observations (*N* = 182).

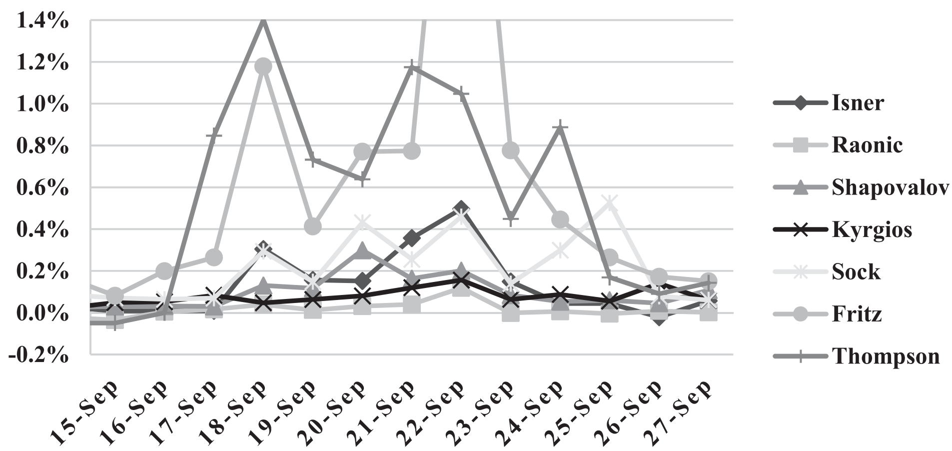

Figure 3. Daily Rate of Change in Athlete Following: Team World. *Note*. The figure illustrates a daily follower growth rate during data collection estimated as a percentage change in comparison to the previous day for athletes on Team World. On September 22, Instagram following for Taylor Fritz grew by 3.2% after a pivotal match where he unexpectedly won against Dominic Thiem.

The figures suggest a general increase in growth rates during the event. The peak days of growth are September 18 (two days before the competition when the Laver Cup hosted an opening 'Laver Cup Welcome to the City' event featuring players) and September 22 (the final day of the event).

In Figure 4, we visualized brand networking by creating a sociogram (Hambrick, 2012). We employed the tags collected throughout all thirteen days of data collection and visualized the relationships using UCINET/NetDraw software (Borgatti et al., 2002). Nodes represent social media accounts, and edges represent the inter-tagging behaviors between the accounts. The width of an edge signals the relationship strength manifested through the frequency of tags connecting the accounts. The sociogram confirms the existence of brand networking between the athletes and the event, signaling the relevance of testing the impact of tagging behaviors on athletes' follower growth. The event brand is positioned at the core of the network as the account with the most links to other accounts, signaling its position as a master brand. The sociogram suggests two sub-networks reflective of the representative teams have formed. Athletes with bigger brands (e.g. Roger Federer, Rafael Nadal) tend to be tagged more often than other athletes,

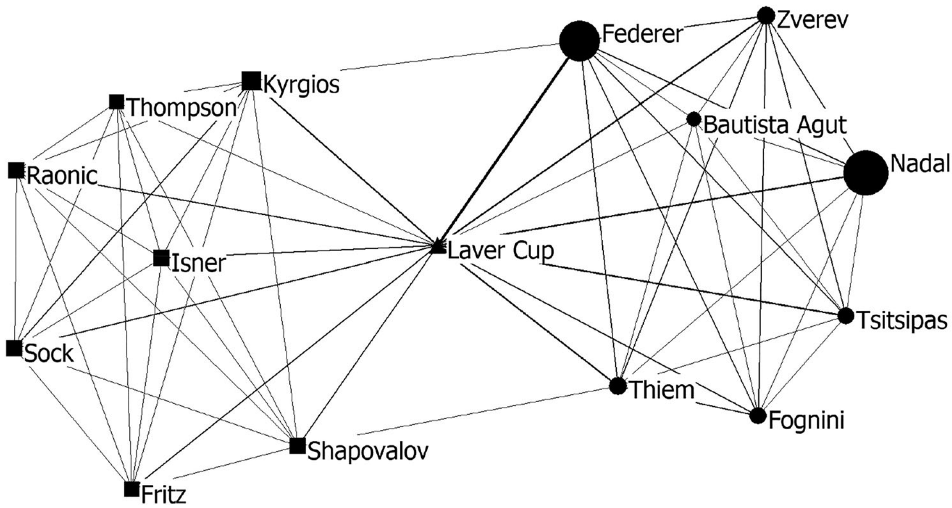

Figure 4. Sociogram of Brand Network During the Event. *N*ote. Square-shaped nodes: Team World athletes. Circular nodes: Team Europe athletes. Triangular node: Laver Cup. The figure illustrates brand relationships during the event. The size of the nodes is adjusted based on the average number of followers for each account during the study period. The width of the edges signals the relationship strength (i.e. frequency of tags connecting the accounts).

highlighting the 'stardom effect' (Watanabe et al., 2016) and the importance of controlling for athletic level (i.e. ranking) and followership size.

Finally, before regression testing, we checked the independent variables for multicollinearity by examining their inter-item correlations and VIFs. All inter-item correlations between explanatory variables were below the recommended cut-off threshold of .80 (Franke, 2010). Correlation between controls TEAM and RANKING was high (.87), likely because Team Europe athletes held higher individual ATP Tour rankings than Team World athletes. However, high correlations between control variables do not impact coefficient estimates of explanatory variables (Srivastava & Gnyawali, 2011; Wooldridge, 2015). Still, to ensure that coefficient estimates and R^2 are not biased because of highly correlated controls, we will compare regressions with two control variables introduced separately and together (Hao et al., 2010). VIFs fell in the range of [1.336; 4.426][1], which is below the cut-off threshold of five (Hair et al., 2005), suggesting no multicollinearity issues were detected.

Table 4. Matrix of Correlations

	Variable	1	2	3	4	5	6	7	8
1	DELTA	1							
2	FOLLOWERS	.796**	1						
3	ATHLETE POSTS	.424**	.168*	1					
4	COMPETITION DAYS	.211**	.000	.191**	1				
5	TAGS BY EVENT	.594**	.383**	.425**	.451**	1			
6	TAGS BY ATHLETES	.603**	.247**	.576**	.258**	.432**	1		
7	TEAM	.514**	.442**	.219**	.000	.198**	.263**	1	
8	RANKING	−.536**	−.509 **	−.263**	.000	−.263 **	−.249**	−.866***	1

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

Table 5. Results of Regression Analyses with Wild-Cluster Bootstrap-SE

	Model 1		Model 2		Model 3			
	Controlling for TEAM		*Controlling for RANKING*		*Controlling for TEAM and RANKING*			
Variable	Step 1	Step 2	Step 1	Step 2	Step 1	Step 2	Hypothesis	Supported
Control Variables								
TEAM	2847.90**	709.04***			1106.08	857.80***	control	
RANKING			−100.00**	−18.53*	−67.739	6.31	control	
Predictors								
FOLLOWERS		6.62E-04***		6.70E-04***		6.68E-04***	H1	✓
ATHLETE POSTS		107.27		111.4		111.30	H2	x
COMPETION DAYS		301.67		308.32		295.64	H3	x
TAGS BY EVENT		236.34***		224.51***		239.40***	H4	✓
TAGS BY ATHLETES		389.59***		401.84***		388.13***	H5	✓
R^2	.264	.852	.287	.847	.297	.853		
Adj. R^2	.260	.848	.283	.842	.289	.847		
F	64.62***	168.3***	72.50***	161.80***	37.83***	144.30***		
ΔR^2		.588***		.560***		.556***		

Note: Dependent variable: daily change in followers (DELTA). *p <.05; **p <.01, *** p <.001. 5,000 iterations.

Regression analysis

The results[2] of the multiple linear regression analyses are presented in Tables 4–5. Models 1 and 2 include TEAM and RANKING as controls separately. Predictors' coefficient estimates were similar in size, sign, and significance between the models. With both controls included in the aggregate regression (Model 3), we obtained similar results, confirming that high correlation between controls did not confound predictors' coefficient estimates (Wooldridge, 2015). We discuss Model 3 results further. Together, controls accounted for 28.9% of the variance in the daily growth of athletes' Instagram followers (Step 1). In Step 2, we added the independent variables. Comparison of the steps using ANOVA indicated a significant increase in variance explained in the dependent variable in Step 2 compared to Step 1 ($F(5) = 131.7$, $p < .001$, $\Delta R^2 = .57$).

Results suggested athlete-related as well as brand-networking-related factors predicted athletes' follower growth. *H1* was supported because there was a positive relationship between the size of athletes' pre-existing social media followings and their daily change in followers. *H2* was not supported because posting frequency did not significantly affect the change in athletes' following. The results did not differ even when we re-analyzed Model 3, adding interaction terms (FOLLOWERS*ATHLETE POSTS) and (RANKING*ATHLETE POSTS) (see online Appendix A). This suggests that the lack of effects of the posting frequency on follower growth did not differ depending on athletes' pre-existing follower count and ranking. *H3* was not supported because the competition days were not a significant predictor of athletes' followers. *H4* was supported because the daily number of times that athletes were tagged by the event was significantly related to athletes' follower growth. Finally, *H5* was supported because there was a positive relationship between the daily number of posts, where athletes were tagged by other athletes, and the daily changes in athletes' following on social media. Overall, results suggest that the increase in athlete following was associated with event-athlete vertical brand influence, athlete-athlete horizontal brand influence, and pre-existing athlete followership size.

Discussion

The study examined the factors influencing athletes' social media brand growth during a non-league event with representative teams. Understanding how athletes can grow their followers is important as athlete brand monetizability is linked to their ability to attract social media followers (Kunkel et al., 2021). Our results demonstrate that the Laver Cup emerged as a sport event brand ecosystem. While controlling for team affiliation and player ranking, we found that brands of participating athletes were impacted by several sources of influence, including pre-existing strength of athlete brands and vertical and horizontal brand networking with the event and athlete brands, respectively.

To examine athlete-central factors of brand growth, we tested the impact of pre-existing athlete social media brand strength operationalized through the number of followers and posting frequency. Addressing *Hypothesis 1*, the analysis showed that the number of pre-existing social media followers had an impact on athlete follower growth, which is consistent with previous findings (Su et al., 2020) and advances knowledge on social media algorithms and consumer behavior (De Veirman et al., 2017; Gaenssle & Budzinski, 2021). This is evident in Table 2 as athletes with stronger brands (e.g. Roger Federer and Rafael Nadal) before the event exhibited higher absolute growth during the event compared to athletes with smaller brands. However, athletes with smaller brands (e.g. Roberto Bautista Agut or Taylor Fritz) benefitted the most relative to themselves, as demonstrated in Figures 2 and 3, showing spikes in growth due to increased visibility from the event and new brand networks. Contrary to *Hypothesis 2*, posting frequency did not affect athlete social media brand growth during the event. This lack of effect did not differ based on ranking or pre-existing following size. The finding helps recognize the differences between personal brand archetypes on social media – i.e. athlete (micro)celebrity versus influencers who grow their brand popularity through high-frequency posting (e.g. Adjei et al., 2012; Gaenssle & Budzinski, 2021). This might be attributed to the fact that during events, participating athletes echo overlapping information (Reynolds et al., 2010). The value of such information is lower than if an athlete was a unique insider. Therefore, athletes are likely to acquire new followers during the event due to consumer interest in the athlete persona rather than content posting frequency (Brison & Geurin, 2021; Vergeer & Mulder, 2019), indicating their social media popularity is an extension of their real-life stardom and fan interest.

To examine the event- and brand-networking-related factors of athlete brand growth, we tested the impacts of competition days and user tagging between athletes and by the event. Addressing *Hypothesis 3*, competition days did not impact athlete follower growth. This finding may be related to the fact that the pre-competition 'Laver Cup Welcome to the City' event generated a lot of social media buzz as athletes posted 'off-field' content (Doyle et al., 2020) in a social rather than an athletic setting, which was of interest to fans. This challenges what is traditionally considered part of a sporting event and highlights the impact of auxiliary events that have primarily business goals, such as servicing sponsors or driving athlete brand growth, reaffirming that the off-field component of athletes' brand images is highly important to fans (cf. Doyle et al., 2020). This shows a strategically integrated 'back-stage' narrative about athletes' lives during the event can be a valuable tactic. In contrast, examining *Hypothesis 4* shows the daily number of times that an athlete was tagged by the event significantly influenced the growth of an athlete's social media following, which empirically confirms that quality master brands can positively impact sub-brands through strategic branding approaches (cf. Kunkel & Biscaia, 2020).

Addressing *Hypothesis 5*, results also indicated that athletes impact each other's brands. Horizontal network collaboration between athlete brands via athlete-athlete tagging contributed to their social media brand growth. These findings address scholarly calls to explore user tagging as a marketing strategy (cf. Su et al., 2020) by highlighting its potential for collaborative cross-promotion among athletes. The illustration of brand networking through network analysis shows athletes formed clear in- and out-groups (Lock & Heere, 2017), as they did not collaborate outside their teams. Since at the Laver Cup, teams are formed based on geography and tennis players participate individually or on other representative teams throughout the year, such networking pattern suggests unused potential to tap into the audiences of other athletes through inter-team athlete-athlete networking.

Contributions

The study advances sport management literature by exploring the combined impact of the vertical and horizontal dimensions of sport brand architecture on the athlete social media brand in an event setting. Specifically, we contribute to scholarship in three major ways. First, we empirically examine brand relationships in the social media context within the sport brand ecosystem (Kunkel & Biscaia, 2020) and extend the conceptualization of sport brand architecture from the league context to the temporal context of a non-league event with representative teams (Kunkel et al., 2013). The study demonstrates the emergence of a sport event brand ecosystem, where the event is a master brand and participating athletes are subbrands. We find that the event brand has a vertical impact on athletes; this relationship is analogous to those within the league brand architecture, where the league brand has an impact on its vertical brand extensions (Kunkel et al., 2014). We also extend the understanding of the position of athlete brands as subbrands impacted by affiliated sports entities (cf. Su et al., 2020).

Second, we demonstrate the existence of horizontal brand relationships between athletes' brands, extending theoretical work on brand relationships within sport brand architecture (Kunkel et al., 2013; Williams et al., 2015). The fact that during the event, athletes' activity on social media impacts the social media brands of other athletes whom they tag in their content underscores the 'coopetitive' nature of athlete-athlete brand relationships. Although rivalry is omnipresent in sports (Havard, 2014), and athletes compete for titles on the field and sponsorship dollars off the field, paradoxically, collaboration enables athletes to maximize the impact of their social media brands. We provide initial insight into the coopetitive nature of relationships between athlete brands, extending the notion of coopetition from sport economics (Robert et al., 2009) and innovation (Wemmer et al., 2016) to the context of strategic athlete branding.

Third, we extend knowledge on athlete brand strategy. Prior sport management literature mainly focused on content analyses (e.g. Emmons & Mocarski, 2014; Geurin & McNary, 2021; Li et al., 2021) or examining consumer behavior in response to athletes' posting patterns (e.g. Doyle et al., 2020; Geurin-Eagleman & Burch, 2016), sparsely discussing the importance of posting regularity and brand relationships. Although social media following represents a paramount asset for athlete monetization (Kunkel et al., 2021), there has been a sparsity of research on how the following can be strategically cultivated (Church et al., 2021). It is a common view that to capitalize on personal branding on social media, individuals need to engage in at-scale content production (Gaenssle & Budzinski, 2021). However, we find that the importance of posting frequency for elite athletes' social media brand growth is not significant. This finding contrasts with arguments made in prior literature on the SMI archetype of human brands (e.g. Duffy & Hund, 2015). Instagram SMIs are known to work strategically toward capitalizing on social media algorithms through high levels of posting frequency and attractive content creation (Gaenssle & Budzinski, 2021). Yet, our findings highlight the importance of prioritizing exposure and strategic brand networking over mere posting frequency (cf. Brison & Geurin, 2021; Vergeer & Mulder, 2019). Athlete brands are amplified by media activities and the spotlight of strong master brands (cf. Su et al., 2020), suggesting athletes' social media brands function differently compared to SMIs, as athletes' popularity appears to depend on other factors such as the ability to build effective brand relationships (cf. Rahikainen & Toffoletti, 2021; Williams et al., 2015).

The current study demonstrates the impact of brand relationships on athletes' social media popularity by focusing on brand networking as a marketing strategy (Duffy & Hund, 2015; Hsiao et al., 2020). We show that brand networking benefits athletes' following by building relationships with other brands that have a similar target market (Zhang et al., 2016). The study contributes to the sparse research on sport consumer behavior in the digital space (Watanabe et al., 2016) by highlighting effective social media branding strategies that entice consumers to follow athletes' on social media.

Managerial implications

The research offers several important implications for industry stakeholders, including event organizers, athletes, and managers. Elite athletes face choices of when and where to compete beyond the league play, including professional, elite amateur, and exhibition events with representative teams. This study provides convincing evidence that highly publicized non-league sporting events can create a platform for athletes to strengthen their social media following, which is an important asset for athlete monetization. New brand networks cultivated at the event are an added reason to participate. Using the example of the Laver Cup brand, we demonstrate that active marketing of athletes on social media by the event, such as featuring athletes in the content and employing the user tagging feature, helps athletes gain exposure to new audiences.

We also demonstrate that athletes can strategically leverage non-league events to expand their social media reach and employ user tagging as an effective marketing tactic for follower growth. Specifically, we find that being tagged by other athletes and the event increases visibility for the tagged athlete, as they get exposed to new audiences. Hence, athletes can collaborate through tagging on social media, which creates a mutually beneficial marketing strategy, allowing athletes to improve their social media brand reach and tap into each other's follower bases. Through collaborations, athletes can co-create their brands to entice fan interest (Doyle et al., 2020).

At the same time, our study illustrates that athletes may gravitate toward networking primarily within their representative team, overlooking the benefits of rivalry that enhances athlete brands (Arai et al., 2013). We recommend that they utilize the non-league events to creatively network with athletes from other teams. However, to maximize the benefits of the event, it is important to reiterate that athletes should work on strengthening their social media presence before entering an event (Su et al., 2020). While events can boost the athlete's social media following, their pre-existing follower count affects their brand growth. For instance, athletes could consider utilizing paid promotions before a sporting event to grow followership beforehand and help maximize the brand benefits from event participation.

Limitations and future research

The current study has five main limitations offering opportunities for future research. First, it was conducted within the context of a single event and a single sport. Although the Laver Cup has a high profile, other major events, such as the Olympic Games, have a long history and tap into national identity (Heere et al., 2013). Such settings may impact subbrands in ways that are different from those we observed. In the future, scholars should examine sports and contexts where representative teams exhibit different levels of development (e.g. FIFA World Cup). Additionally, whereas our research focused on a context where representative teams do not have their own social media accounts, other teams may have their own account (e.g. USWNT) or share it with a different team (e.g. Canadian men's and women's national soccer teams share an Instagram account). This could lead to additional horizontal (i.e. team-team) and vertical (e.g. event-team; team-athlete) brand networking. Future research could examine the effects of such brand dynamics.

Second, due to the team format and the specificity of the match schedule, participation in the Laver Cup allowed athletes to be spotlighted throughout the event. Yet, other events may include an elimination element. For instance, the FIFA World Cup features a knockout stage after a group stage. Examining the context of an elimination event would allow seeing how athletic performance impacts athletes' social media brand and whether/how branding-related factors can help overcome or enhance the effects of poor athletic performance. Third, we focused on the number of followers as a proxy for brand growth. Yet, an athlete's brand strength is manifested in multiple ways beyond the number of followers. Therefore, future research should examine what drives engagement and fandom during the event as a proxy for relationship strength (cf. Brison & Geurin, 2021).

Fourth, following Su et al.'s (2020) approach, we tracked athletes' social media following and posting for thirteen days. Whereas our findings show that all athlete brands grew their following, we have no information on whether this asset will be sustainable over time as less committed and interested followers may drop out. Future research should consider tracking athletes over longer periods and segment fans to examine not only the number of new followers but also how engaged they are. Fifth, we demonstrate the insignificant effects of posting frequency on athlete brand popularity on Instagram during the event. In the future, it would be interesting to investigate the boundary conditions of such effects (i.e. what is 'frequent enough' to obtain popularity), as well as the importance of frequency relative to different types of content (cf. Torbarina et al., 2020).

Conclusion

This research extends the sport management literature by investigating the impact of an event and manageable branding activity on athletes' social media brand growth. Using longitudinal behavioral data, we demonstrate the benefits of brand networking via user tagging as a marketing strategy to increase athletes' following. Athletes' pre-existing followership size, the event's social media activities, and athletes' 'coopetitive' relationships with other participating athletes were predictors of athletes' follower growth. This research highlights the importance of non-league sport events with representative teams as strategic opportunities for athletes to grow their social media brands through vertical and horizontal brand relationships, thereby contributing to sport brand theory and practice.

Notes

1. VIFs for all explanatory variables were under 1.809 across models. VIFs for controls TEAM and RANKING were 1.297 and 1.403 when introduced separately, and 4.090 and 4.426 when introduced together.
2. After conducting the multiple linear regression with the wild-cluster bootstrap-*SE*, we compared the results with CRSE estimation. In terms of significance/insignificance of estimates, results were similar although there were slight differences in estimates of standard errors and regression coefficients. We base our discussion on the results of the wild-cluster bootstrap-*SE* procedure, which is considered more robust in such a setting (Cameron et al., 2008).

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ORCID

Nataliya Bredikhina http://orcid.org/0000-0001-7097-4327
Keshav Gupta http://orcid.org/0000-0002-4834-0261
Thilo Kunkel http://orcid.org/0000-0002-1607-0148

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