MODELING ENVIRONMENTAL ANTECEDENTS OF ONLINE WORD-OF-MOUTH ON TEAM SOCIAL MEDIA: A PERSPECTIVE OF INFORMATION VALUE

by

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ABSTRACT

The current study explored the environmental antecedents of online word-of-mouth on team social media from the perspective of information value. A content analysis and multiple regression analysis were conducted to assess the influence of two dimensions of information value (i.e., content provision and game attractiveness) on high- and low-strength online word-of-mouth behavior. The findings confirmed the crucial role of information value in determining fans' online word-of-mouth behavior, providing a new theoretical approach for analyzing this phenomenon in the context of sport marketing communications. Actionable suggestions are implicated in terms of capitalizing important environmental variables to maximize the economic and marketing benefits of online word-of-mouth.

INDEX WORDS: Online Word-of-Mouth, Environmental Antecedents, Team Social Media, Information Value

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CHAPTER 1

INTRODUCTION

Word-of-mouth (WOM) refers to "informal communications directed at other consumers about the ownership, usage, or characteristics of particular goods and services or their sellers" (Westbrook, 1987, p. 261), such as product-related discussion, usage information sharing, recommendations, and product mentions. The benefits of WOM have been extensively identified and tested in various marketing studies. For instance, WOM has been recognized as a more credible and trustworthy marketing tool than conventional advertising (Engel, Kegerreis, & Blackwell, 1969; Trusov, Bucklin, & Pauwels, 2009). WOM can provide a new channel for marketers to reach consumers (Duan, Gu, & Whinston, 2008), capture the attention of potential consumers (Trusov, Bucklin, & Pauwels, 2009), promote the adoption of new products (Arndt, 1967; Engel et al., 1969), sway post-purchase product perceptions (Bone, 1995), facilitate re-consumption behavior (Villanueva, Yoo, & Hanssens, 2008), and influence fans' perceived brand association (Shreffler & Ross, 2013).

Differing from traditional face-to-face WOM, online WOM extends interpersonal communication to online social networks such as bulletin boards, chat rooms, instant messenger clients, and social media sites, largely reducing geographic, time, and linguistic constraints (Berger, 2014). Especially, the pervasion of social media in sport team communication further stimulate and escalate online WOM among fans. For example, 21 million fans liked the Los Angeles Lakers' Facebook page in 2016, and each Facebook user had, on average, around 350 online friends (Statista, 2014). If properly managed, a great amount of online WOM could be activated and further circulated among fan's online social networks, largely amplifying the benefits of traditional face-to-face WOM.

Accordingly, developing strategies to promote online WOM behavior has been a crucial and attractive research agenda in recent decades. Although the existing sport marketing literature has laid a solid foundation in identifying WOM antecedents, two gaps in this research area exist and require further investigation. First, most studies have focused on intangible psychological variables (e.g., satisfaction, loyalty, commitment, trust, and perceived value), whereas findings about observable and manipulable antecedents of WOM are limited. Second, although WOM behavior has different strengths, ranging from mere product mentions to strong recommendations, few studies have distinguished between these strength levels when exploring the environmental antecedents of WOM behavior. Building upon the product value theory, the current study explored observable antecedents of WOM within the domain of information value and investigated their influences on both high- and low- strength WOM behavior (i.e., Like and Share behavior) in a natural online setting (i.e., Facebook pages of professional sport teams).

Research Hypotheses

The study examined the following hypotheses:

1. Post content will influence fans' Like behavior on Facebook.
2. Time schedule of information supply will influence fans' Like behavior on Facebook.
3. Information format will influence fans' Like behavior on Facebook.
4. Team history and reputation will influence fans' Like behavior on Facebook.
5. Player quality will influence fans' Like behavior on Facebook.
6. Team quality will influence fans' Like behavior on Facebook.
7. Game closeness will influence fans' Like behavior on Facebook.

8. Broadcast schedule will influence fans' Share behavior on Facebook.
9. Local market size will influence fans' Share behavior on Facebook.
10. Win/loss situation will influence fans' Share behavior on Facebook.

Research Delimitations

1. This study only focused on fans' online WOM on the platform of Facebook.
2. This study focused on online WOM about the NBA based on the following two considerations. First, the NBA is one of the most representative sport leagues in the United States, therefore the findings would shed some light to other U.S. based professional leagues such as the National Football League, the Major League Baseball, and the National Hockey League. Second, limiting the research focus on the NBA would well define boundary conditions of research findings.

Research Limitations

The following limitations have been acknowledged in the current study:

1. Additional research is necessary to replicate the results of this study in alternate contexts.
2. This study only collected data in a limited time period (i.e., first week of November, December, March, and April of the 2015-16 regular season), which might weaken the representativeness of data.
3. This study only collected data from a limited number of NBA teams (i.e., Atlanta Hawks, Houston Rockets, Chicago Bulls, Phoenix Suns, and Los Angeles Clippers)
4. The current study did not control fans' psychological (team identification, satisfaction, attitude) and interpersonal factors (e.g., peer pressure) when examining the influences of environmental antecedents on online WOM.

CHAPTER 2

REVIEW OF LITERATURE

Social Media and Online Sport Communication

In the past decade, the popularity of social media has largely reshaped the landscape of sport marketing communications. First, social media reduces the geographic, time, and linguistic constraints of traditional communication, enabling marketers to attract a larger fan-base. Second, the social networks of various users can escalate the speed and scale of message delivery (Yang & Leskovec, 2010; Zhou, Bandari, Kong, Qian, & Roychowdhury, 2010). The shared content can be viewed and re-shared by other social media users who have not directly followed sport teams. Accordingly, various sport entities, including sporting governing bodies, professional sport teams, event organizers, athletes, and sport journalists, have begun to use social media platforms to communicate with their internal and external shareholders (Armstrong, Delia, & Giardina, 2014; Clavio & Kian, 2010; Eagleman, 2013; Frederick, Burch, & Blaszka, 2015; Hambrick, Simmons, Greenhalgh, & Greenwell, 2010). As an important marketing communication tool, the merits of social media in relationship management (e.g., Eagleman, 2013; Filo, Lock, & Karg, 2014; Waters, Burke, Jackson, & Buning, 2011; Williams & Chinn, 2010), sport branding (e.g., Geurin & Burch, 2017; Pfahl, Kreutzer, Maleski, Lillibridge, & Ryznar, 2012), and information dissemination (e.g., Hambrick, 2012; Yang & Leskovec, 2010) have been widely acknowledged. Given the characteristics of professional sports, such as a huge fan-base, highly noticeable product, and perishable information content, social media is likely to help professional teams engage fans and spread team information with ease.

Information Value as an Antecedent of Online WOM

As the foundation of all marketing activity (Holbrook, 1994), product value is the "consumer's overall assessment of the value of a product based on perceptions of what is received and what is given" (Zeithaml, 1988, p. 14); in other words, product value involves a trade-off between benefits or gets (e.g., quality, convenience, and volume) and costs or gives (e.g., money, time, and effort). A high ratio of benefits to costs leads to high perceived value, which further produces psychological fulfillment and promotes purchase intention. Previous studies have identified three dimensions of product value: (a) functional value refers to the objective and instrumental usefulness of product attributes (e.g., durability, quantity, and sturdiness) that are used to solve practical and task-related problems; (b) hedonic value emphasizes intrinsic attributes that provide multi-sensory and affective benefits (e.g., pleasure, emotion, and stimulation); and (c) symbolic value involves the extrinsic social meanings of products that fulfill people's personal and social needs (e.g., self-expression and outer-directed self-esteem) (Bhat & Reddy, 1998; Mathews, Ambroise, & Brignier, 2009; Park, Jaworski, & Maclnnis, 1986; Smith & Colgate, 2007).

Extending the concept of product value to the field of sport information, the information value was conceptualized as fans' overall assessment of the utility of sport information. As an important subset of sport products (Pedersen, Miloch, & Laucella, 2007; Pedersen & Thibault, 2014), sport information is characterized by both hedonic and symbolic value. In terms of hedonic value, sport information helps fans experience the excitement and eustress created by the uncertainty of sport events, temporarily escape from everyday life, and appreciate the aesthetic components of performance (James, Trail, Zhang, Wann, & Funk, 2006). Given that sport information consumption is noticeable enough to attract attention, meaningful enough to evoke reaction, and well-controlled by consumers, sport information has rich symbolic value for one's socialization (e.g., creating or reinforcing group affiliation, acquiring social roles, connecting with others, and strategically expressing self-concepts).

The driving force of product value in promoting WOM behavior has been well documented in both mainstream businesses (e.g., Gruen, Osmonbekov, & Czaplewski, 2006; Hartline & Jones, 1996; McKee, Simmers, & Licata, 2006) and sport businesses (e.g., Bennett, Ferreira, Lee, & Polite, 2009; Byon, Zhang, & Baker, 2013; Min, Zhang, Kim, & Kim, 2014; Swanson, Gwinner, Larson, & Janda, 2003). Specifically, Min et al. (2014) found that perceived value exerted a strong influence on the WOM behavior of fans who attend women's basketball events. Swanson et al. (2003) revealed that the symbolic value of an event (e.g., group affiliation and self-esteem enhancement) positively impacted consumer WOM intention. Bennett et al. (2009) and Byon et al. (2013) confirmed the positive relationship between perceived value (in terms of importance and relevance) and consumption intention, of which WOM is a major component.

Similar effects have been found for the information product. As indicated by Sears and Freedman (1967), high information value increases receivers' desire to be exposed to the communication content. High information value has also been shown to promote the receivers' positive attitude towards the information releaser (Bauer, Reichardt, Barnes, & Neumann, 2005; Szymanski & Hise, 2000). Given that positive perception and attitude are major antecedents of WOM (Brown, Barry, Dacin, & Gunst, 2005; De Matos & Rossi, 2008), high information value should promote fans' online WOM behavior.

Factors Determining Information Value

Content Provision

“Content is king” is a widespread tenet of effective online communication, underscoring the importance of being a significant content provider in digital marketing (Pulizzi & Barrett, 2008). Appealing content offered by marketing entities could effectively inform and educate target consumers about products by providing them with foundational and necessary information, promoting product engagement, strengthening brand attachment, and raising usage gratification (Carlson & O'Cass, 2010; Cristobal, Flavián, & Guinalíu, 2007; Ladhari, 2010; Lieb, 2011). That is, appropriate content supply can increase perceived information value by increasing its positive “get” components and mitigating its negative “give” components. This function of information content has been largely amplified by internet technology. Social media platforms provide professional sport teams with effective and efficient communication channels to deliver supplementary content about sport competition. Unlike onsite delivery or live broadcast signals, which are highly standardized, social media outlets give team managers more freedom to create attractive message content to increase perceived information value.

Given the contextual nature of digital content (Koiso-Kanttila, 2004; Rowley, 2008), the ways in which audiences interpret and perceive the same content can vary with different physical environments, time, information formats (e.g., words, images, and videos), and technologies (e.g., endpoint devices, Internet service, and media platforms). Except for some constants (e.g., Facebook platform in the current study) or variables outside the scope of the current study (e.g., endpoint devices, Internet service, and physical environments), marketers are still controlling when to supply the information and how to format it. Both of them could add information value when effectively managed. As shown in the sport-economics literature, the market demand for game viewership and attendance varies according to time/schedule such as days of the week and months of the year (Boyd & Krehbiel, 1999, 2003; Tainsky & McEvoy, 2012; Tainsky, Salaga, & Santos, 2013; Watanabe, 2012). Games scheduled on the weekend, or at the beginning of the season, are usually perceived to be more valuable because of fans' time availability and psychological needs. Since team-related information is the derivative product of sport events, its value is also expected to be influenced by the time factor. In terms of information format, it is expected that words, images, and videos would provide users with different perceptions of information value (e.g., informativeness, convenience, and visualization). Accordingly, hypotheses 1 and 2 in this study were proposed:

H1: Post content will influence fans' Like behavior on Facebook.

H2: Time schedule of information supply will influence fans' Like behavior on Facebook.

H3: Information format will influence fans' Like behavior on Facebook.

Game Attractiveness

Given the contextual nature of digital content (Koiso-Kanttila, 2004; Rowley, 2008), the perceived value of online sport information might depend on game attractiveness (i.e., the degree to which an event is noteworthy). Higher game attractiveness usually indicates a higher level of hedonic information value. For example, a close game creates more excitement and eustress, and the participation of star players in a game increases aesthetic appeal and value of time spent. Meanwhile, higher game attractiveness also captures tremendous social attention among peers, colleagues, and family, increasing the symbolic value of sport information (e.g., self-expression). In the context of professional sports, game attractiveness has been widely considered one of the core service quality factors in spectator sport and has been shown to exert a positive influence on game-related consumption (Byon et al., 2013; Byon, Zhang, & Connaughton, 2010; Schofield, 1983; Zhang, Pease, Hui, & Michaud, 1995).

Given the intangible attributes of game attractiveness, a large number of studies on market demand have sought to model this latent construct. Measurements of game attractiveness can be generally categorized into two categories: psychometrics and econometrics. The psychometric approach typically adopts a survey-based research design in which participants are requested to rate their perceptions of game-related variables on Likert-type scales (e.g., Byon et al., 2010; Greenwell, Fink, & Pastore, 2002; Zhang, Lam, & Connaughton, 2003; Zhang et al., 1995). The econometric approach typically relies on observable variables in a natural setting (e.g., Salaga & Tainsky, 2015; Tainsky, 2009; Tainsky et al., 2013; Watanabe, Yan, & Soebbing, 2015, 2016). Overall, the following environmental factors have been frequently used to measure game attractiveness in both approaches: team history and reputation, player quality, team quality, game closeness, and game schedule (e.g., home/away game, holiday/non-holiday game, day/night game) (Byon et al., 2010; Greenwell et al., 2002; Salaga & Tainsky, 2015; Tainsky, 2009; Tainsky et al., 2013; Watanabe et al., 2015, 2016; Zhang et al., 2003; Zhang et al., 1995). Additionally, the econometric approach frequently uses variables such as broadcast schedule (i.e., nationally televised/not nationally televised), local market size, and win/loss situation when assessing sport media demand (Brown & Sauer, 1993; Tainsky, Xu, & Zhou, 2014; Watanabe et al., 2015, 2016). These variables will also likely to influence fans' online WOM behavior, the subset of media consumption.

Unlike the demand for a television broadcast or a live event, which is largely dependent on game day circumstances, online WOM behavior usually continues even after a game has ended. Therefore, the aforementioned dimensions of game attractiveness should continue influencing online WOM behavior until a subsequent event creates a new situation of game attractiveness.

H4: Team history and reputation will influence fans' Like behavior on Facebook.

H5: Player quality will influence fans' Like behavior on Facebook.

H6: Team quality will influence fans' Like behavior on Facebook.

H7: Game closeness will influence fans' Like behavior on Facebook.

H8: Broadcast schedule will influence fans' Share behavior on Facebook.

H9: Local market size will influence fans' Share behavior on Facebook.

H10: Win/loss situation will influence fans' Share behavior on Facebook.

CHAPTER 3

METHOD

Study Design

The current study was conducted using National Basketball Association (NBA) teams' Facebook data. With $5.2 billion in revenue and a 13% annual growth rate in 2015, the NBA is one of the premier professional sport leagues in the world (Forbes Corporate Communications, 2016). Facebook has remained one of the most popular social media platforms in the sport industry (Statista, 2014). Considering the effect size and statistical power of research findings, the number of independent variables, team characteristics, and event schedule, this study collected the Facebook data of five representative NBA teams (i.e., Atlanta Hawks, Houston Rockets, Chicago Bulls, Phoenix Suns, and Los Angeles Clippers) in particular time slots (i.e., first week of November, December, March, and April of the 2015-16 regular season). Specifically, the effect size (Cohen's $f^2 = .10$), statistical power ($\pi = .80$), and number of independent variables (N =28) were used to estimate the required sample size. Selection of five teams was based on team performance, market size, and conference affiliation (see Table 3.1). National holidays and special events (e.g., events of All-Star Weekend) were excluded in the selection of time slots. Each Facebook post was treated as a single data entry. As a result, a total of 526 cases were collected.

Measurement

Independent Variables

In the domain of content provision, independent variables were selected in aspects of post content, information format, and time schedule of information supply. The current study measured post content in two ways: star power of post content and content theme. To measure the star power of players mentioned or shown in post content, ESPN star power rankings for the 2015-16 season were used. Considering the cross-sectional nature of ESPN star power rankings and the performance fluctuation of players, the rank of each player was recorded by rounding to the next ten. For example, a 5th-ranked player was coded with a value of 10, and a 132nd-ranked player was coded with a value of 140. Non-NBA players and new players who were not included in the rankings were coded with a value of 400 (i.e., the lowest possible ranking). Retired players ranked in the top 100 players by ESPN were coded with a value of 10; retired players who were not ranked were coded with a value of 400. If a post involved multiple players, the player with the highest rank was recorded. Because no typology for categorizing content themes of Facebook data was available at the time of data collection, a pilot study (i.e., content analysis described later) was conducted to establish a typology.

Regarding the time schedule of information supply, Boyd and Krehbiel (1999, 2003) indicated that whether a game was scheduled on a weekday or a weekend significantly impacted consumer demand of that game. Watanabe (2012) indicated that this dichotomous game schedule variable (i.e., weekday or weekend) should be further divided into specific days of the week. Tainsky and McEvoy (2012), Tainsky et al. (2013), and Watanabe et al. (2015) also suggested that game timing should include the months of a given season. Accordingly, this study used days of the week and months of the year to measure the time schedule of information supply. Six dummy variables were created to represent Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday, which were compared with Monday (i.e., reference group). Three dummy variables were created to represent December, March, and April, which were compared with November (i.e., reference group). The category of information format was also examined and established in the pilot study (i.e., content analysis).

In the domain of game attractiveness, to measure team reputation, team history, and local market size, the current study used the 2015-16 Forbes Ranking of NBA team valuations (Forbes Corporate Communications, 2016), which combined the values for city and market size, arena, brand, and league-wide revenue sharing. Player quality was assessed by counting the number of all-star players in one game. Team quality was measured using the ESPN weekly power rankings of home and away teams. In addition, based on suggestions from previous studies that the playoff appearance of the home team impacted fans' sport demand (e.g., Tainsky et al., 2014; Watanabe et al., 2015), whether the home team was a playoff contender was used to evaluate team quality. A dummy variable was created to represent the playoff contender (i.e., a team ranked in the top 10 of the Eastern or Western Conference). Game closeness was assessed both before and after the game. The former was measured by the ranking differential (i.e., ESPN weekly power rankings) between the home and away teams (e.g., Salaga & Tainsky, 2015; Watanabe et al., 2015), and the latter was measured by the score differential of a game (e.g., Paul, Wachsman, & Weinbach, 2010; Tainsky, Kerwin, Xu, & Zhou, 2014). Since no national holiday occurred during the selected time slots and because issues related to day/night scheduling (e.g., time and temperature constraints) seldom impact online WOM behavior, game schedule was measured using only a dummy variable to designate "home" or "away." In terms of broadcast schedule, whether a game is nationally televised has been shown to impact consumer demand for social media (Watanabe et al., 2015); therefore, a dummy variable designating "nationally televised game" was created. Based on the win/loss typology suggested in previous studies (e.g., Brown & Sauer, 1993; Watanabe et al., 2015), four types of win/loss situations were created: losing one game, losing streak (i.e., losing two or more games in a row), winning one game, and winning streak (i.e., winning two or more games in a row). Three dummy variables (i.e., losing streak, winning one game, and winning streak) were created and compared with the situation of losing one game (i.e., reference group).

Dependent Variables

In the current study, the dependent variables were observable online WOM behaviors. To avoid function-bias (i.e., when a function is available on only one or very few social media platforms), the function variables that are available on major social media platforms (e.g., Facebook, Twitter, Google+, and YouTube) were considered. Two appropriate types of online WOM behavior emerged: Like and Share. When a Facebook user shares a post, it appears on his/her timeline, viewable by his/her Facebook Friends, who then have the option to add a comment or reshare. When a Facebook user likes a post, his/her emotional reaction is shown on the post, but the post itself is not disseminated to his/her Facebook network. According to Godes and Mayzlin (2004), the informativeness of WOM can be measured by volume (i.e., how much information is there) and dispersion (i.e., how widely the WOM is spread). In the current study, the shared content usually has a much wider dispersion and slightly richer information volume than the liked content. Therefore, sharing is a higher-strength online WOM behavior that is more engaging, visible, and influential in sport communication than liking. That is, sharing is a high-strength online WOM in this study, while liking is the one with low-strength. In the study, the numbers of Like and Share of a post were recorded as the dependent variables.

Pilot Study

As a systematic method for identifying core and consistent meanings from textual or visual media messages (Patton, 2012; Rubin, Rubin, & Haridakis, 1993), content analysis has been widely used in sport communication studies (e.g., Geurin-Eagleman & Burch, 2016; Hambrick et al, 2010; Scott, Hill, & Zakus, 2012; Wallace, Wilson, & Miloch, 2011). Therefore, content analysis using the collected data was used to establish categories for the two independent variables in the domain of content provision (i.e., content theme and information format).

Based on the grounded theory (Strauss & Corbin, 1990), content schemas were systematically extracted from the data through constant comparison. Once theoretical saturation was achieved (Lindlof & Taylor, 2011; Scott et al., 2012), six content schemes had emerged, and a codebook was developed (see Table 3.2)

To assess reliability of proposed content schemes, two researchers with extensive background in sport communication and content analysis worked independently to categorize some randomly selected data (i.e., data from December and April) into the six content schemes. Holsti's coefficient of reliability (see equation below) for the six content themes ranged from 83.3% to 92.7%, suggesting good inter-coder reliability (Holsti, 1969):

$$R = \frac{2M}{N_1 + N_2}$$

Where M refers to the number of coding decisions agreed upon by the two coders and N_1 and N_2 refer to the total number of coding decisions made by the first coder and second coder, respectively. Disagreements were resolved through discussion between the two coders. Consequently, the six mutually exclusive content schemes were finalized. Five dummy variables (i.e., team status, pre-game promotion, game highlight, game summary, and other off-court promotion) were created and compared with corporate social responsibility (CSR).

During the pilot study, two types of information format were also identified: (a) image-based content (i.e., image with words) and (b) video-based content (i.e., video with words). A dummy variable was created to compare image-based content to video-based content (1 = image-words, 0 = video-words).

Data Analysis

Structural Equation Modeling (SEM)

SEM analysis has been widely favored in the behavioral research due to multiple condensations. First, it provides estimates for both the measurement model (between a latent factor and its indicators) and the relationship/structural model (among latent factors and observed variables). By doing this, the biases attributable to random error and construct-irrelevant variance could be effectively corrected (Tomarken & Waller, 2005). Second, global fit indices (e.g., comparative fit index, root mean square error of approximation, and standardized root means square residual) can provide "a summary evaluation of even complex models that involve a large number of linear equations" (Tomarken & Waller, 2005, p.34).

Besides above-mentioned advantages of SEM analysis, the statistical solution of SEM was used based on the following considerations: First, within domains of content provision and game attractiveness, there were multiple sub-dimensions and relevant observed variables. For example, the sub-dimension of time schedule of information supply was measured by both days of the week and months of the year; the sub-dimension of game closeness was assessed by the ranking differential between the home and away teams and the score differential of a game; the win/loss situation was measured by losing one game, losing streak (i.e., losing two or more games in a row), winning one game, and winning streak (i.e., winning two or more games in a row). Second, there are two dependent variables (like and share behavior) in the current study. Third, the sample size is big enough to accommodate the SEM analysis: (1) ratio of cases and number of independent variables was over 18:1, meeting the suggested 10 cases per variable (Hair, Black, Babin, & Anderson, 2010) and (2) the total case number (N = 526) was over the suggested minimum size of 200 (Anderson & Gerbing, 1998; Hair et al., 2010; Harris & Schaubroeck, 1990; Weston & Gore, 2006).

Both the Shapiro-Wilk statistics ($p < .001$) and the normal probability plot suggested that the distribution of the two dependent variables was non-normal. To address this issue, the MLR estimator in Mplus 7.0, a modified maximum likelihood estimation, was used. This method estimates standard errors using a sandwich estimator to determine whether the chi-square statistic asymptotically equals the Yuan-Bentler T2* test statistic (Muthen & Muthen, 2012); therefore, the MLR estimator is robust when handling non-normal data with heteroscedasticity (Muthen & Muthen, 2012; White, 1980).

However, in SEM analysis, the model could not converge. According to the Muthen & Muthen, (2012), non-convergence of model estimation might be caused by: (1) the low value of maximum number of iterations and (2) problems in optimizing the fitting function. The first type of issue could be addressed by changing the number of maximum number of iterations in the coding stage. The second type of issue could be attributed to the inappropriateness of staring value and the differences in measurement scales. In terms of staring value, the dataset was re-examined and no problematic starting value was detected. In terms of measurement scales, the current study used different types of variables (including both continuous and categorical variables) and quite different measurement scales (e.g., the huge difference between the number of like and the range of team rank). As Muthen & Muthen (2012) indicated, non-convergence issues would take place when “the range of sample variance values greatly exceeds 1 to 10” and when the date includes both continuous and categorical variables (p. 468). Therefore, with characteristics of current data, the solution of SEM was inappropriate in this study.

In addition, this study also tried path analysis in which the observed variables rather than latent factors were directly used in model estimation. In other word, there is only the relationship/structural model and no measurement model. However, with the issue of different measurement scales, the estimation of path analysis also could not converge. To address this issue, multiple regression analysis which is much robust in dealing with different types of variables and measurement scales was finally used (Hair et al, 2010).

Multiple Regression Analysis

Check of Assumptions and Data Modification

Three cases were excluded due to their inferior Mahalanobis distance from the suggested outlier cut-off value for multivariate data (i.e., chi-square distribution with $df = 28$, $p < .01$). Linearity of the proposed model was confirmed by the clear linear shape of the residual scatterplot. The correlation matrix showed that all univariate correlations among the independent variables were well below .600, indicating low-collinearity at the univariate level (Hair et al., 2010). All VIF values of independent variables were lower than or close to 5.0, suggesting an acceptable level of multicollinearity among the data (Hair et al., 2010; Montgomery, Peck, & Vining, 2001). Both the Shapiro-Wilk statistics ($p < .001$) and the normal probability plot suggested that the distribution of the two dependent variables was non-normal. To address this issue, the MLR estimator in Mplus 7.0, a modified maximum likelihood estimation, was used. This method estimates standard errors using a sandwich estimator to determine whether the chi-square statistic asymptotically equals the Yuan-Bentler T2* test statistic (Muthen & Muthen, 2012); therefore, the MLR estimator is robust when handling non-normal data with heteroscedasticity (Muthen & Muthen, 2012; White, 1980).

Regression Method

As to the regression estimation methods, there are two general categories: confirmatory specification and sequential specification. In the former one, researchers have specified independent variable before estimation based on strong theoretical foundations. In other words, the selection of independent variables was based on pre-existing theories and is subjected to the total control of researchers (Hair et al, 2010). With more independent variables, the regression model usually produces higher predictive accuracy. In the sequential specification, researchers first generate a pool of independent variables and sequentially select (e.g., stepwise estimation, forward addition, and backward elimination) variables based on their statistical properties (i.e., significantly increase the predictive accuracy) (Hair et al, 2010). Given that the current study was more interested in maximizing overall predictive power and the selection of independent variables was backed up by the solid theoretical framework (i.e., information value), the confirmatory specification was in the multiple regression analysis.

Model Specification

The following two equations represent the linear model used to estimate the results from the dataset, where β_0 is the constant term and ε is the equation error term. Descriptions of the independent variables were provided in Table 3.3.

$$
\begin{aligned}
Like = \ & \beta_0 + \ \beta_1 Cont\_star + \ \beta_2 Team\_stat + \beta_3 Game\_prom + \beta_4 Game\_high \\
& + \beta_5 Game\_summ + \beta_6 Off\_prom \ + \beta_7 Image + \beta_8 Tue + \beta_9 Wed + \beta_{10} Thu \\
& + \beta_{11} Fri + \beta_{12} Sat + \beta_{13} Sun + \beta_{14} Month\_12 + \beta_{15} Month\_3 + \beta_{16} Month\_4 \\
& + \beta_{17} Team\_value + \beta_{18} Allstar + \beta_{19} Po\_cont + \beta_{20} Home\_rank \\
& + \beta_{21} Away\_rank + \beta_{22} Rank\_diff + \beta_{23} Score\_diff + \beta_{24} Home\_game \\
& + \beta_{25} Nation\_tv \ + \beta_{26} Loss\_s \ + \beta_{27} Win\_1 + \beta_{28} Win\_s + \varepsilon
\end{aligned}
$$

$$
\begin{aligned}
Share = \ & \beta_0 + \ \beta_1 Cont\_star + \ \beta_2 Team\_status + \beta_3 Game\_prom + \beta_4 Game\_high \\
& + \beta_5 Game\_summ + \beta_6 Off\_prom \ + \beta_7 Image + \beta_8 Tue + \beta_9 Wed + \beta_{10} Thu \\
& + \beta_{11} Fri + \beta_{12} Sat + \beta_{13} Sun + \beta_{14} Month\_12 + \beta_{15} Month\_3 + \beta_{16} Month\_4 \\
& + \beta_{17} Team\_value + \beta_{18} Allstar + \beta_{19} Po\_cont + \beta_{20} Home\_rank \\
& + \beta_{21} Away\_rank + \beta_{22} Rank\_diff + \beta_{23} Score\_diff + \beta_{24} Home\_game \\
& + \beta_{25} Nation\_tv \ + \beta_{26} Loss\_s \ + \beta_{27} Win\_1 + \beta_{28} Win\_s + \varepsilon
\end{aligned}
$$

Table 3.1

Description of NBA Teams Selected for the Current Study

Teams	Team information in 2015-16 regular season
Atlanta Hawks	Above average performance, 7th in the league-wide ranking; playoff appearance; relatively small market, 22nd in home game attendance; Eastern conference
Houston Rockets	Medium performance, 17th in the league-wide ranking; playoff appearance; medium market, 15th in home game attendance; Western conference
Chicago Bulls	Medium performance, 16th in the league-wide ranking; out of playoff; large market, 1st in home game attendance; Eastern conference
Phoenix Suns	Below-average performance, 27th in the league-wide ranking; out of playoff; relatively small market, 20th in home game attendance; Western conference
Los Angeles Clippers	Above average performance, 6th in the league-wide ranking; playoff appearance; large market, 10th in home game attendance; Western conference

Table 3.2

Content Themes Identified through Content Analysis

Corporate social responsibility (CSR)	According to McWilliams, Siegel, and Wright (2006), CSR refers to "actions that appear to further some social good, beyond the interests of the firm and that which is required by law" (p. 1). In the current study, CSR includes content about practices in environmental conservatism, philanthropy, volunteering, etc.
Team status	Content about honor records of players, personnel changes, injury reports, arena renovations, and team training information
Pre-game promotion	Content about game schedule, incentives for game attendees, attendees' dress code, game broadcast information, etc.
Game highlight	Content showing a replay of one or multiple spectacular plays in one or multiple games
Game summary	Content summarizing one game or multiple games via score reports, player interviews, coach reports, analytical reports, etc.
Off-court promotion	Content about promotional activities other than CSR, such as promotion of non-basketball events, coupon promotions, interactive questions, ceremony information (e.g., rewards for team management or retired players), promotion of other local teams

Table 3.3

Selected Variables and Their Descriptions

Variable	Description
Cont_star	Star power of post content based on 2015-16 ESPN rankings
Team_stat	Content theme of team status (dummy variable, 1 = yes, 0 = CSR)
Preg_prom	Content theme of pre-game promotion (dummy variable, 1 = yes, 0 = CSR)
Game_high	Content theme of game highlight (dummy variable, 1 = yes, 0 = CSR)
Game_summ	Content theme of game summary (dummy variable, 1 = yes, 0 = CSR)
Off_prom	Content theme of off-court promotion (dummy variable, 1 = yes, 0 = CSR)
Image	Image-based content (dummy variable, 1 = yes, 0 = video-based content)
Tue	Tuesday (dummy variable, 1 = yes, 0 = Monday)
Wed	Wednesday (dummy variable, 1 = yes, 0 = Monday)
Thu	Thursday (dummy variable, 1 = yes, 0 = Monday)
Fri	Friday (dummy variable, 1 = yes, 0 = Monday)
Sat	Saturday (dummy variable, 1 = yes, 0 = Monday)
Sun	Sunday (dummy variable, 1 = yes, 0 = Monday)
Month_12	The first week in December (dummy variable, 1 = yes, 0 = the first week in November)
Month_3	The first week in March (dummy variable, 1 = yes, 0 = the first week in November)
Month_4	The first week in April (dummy variable, 1 = yes, 0 = the first week in November)
Team_value	Team value: 2015-16 Forbes team valuation ranking (larger number means lower ranking)
Allstar	Number of all-stars in one game
Po_cont	Playoff contender (dummy variable, 1 = yes, 0 = not a playoff contender)
Home_rank	Home team ranking: ESPN weekly power ranking of home team (larger number means lower ranking)
Away_rank	Away team ranking: ESPN weekly power ranking of away team (larger number means lower ranking)

Rank_diff	Ranking difference: weekly ranking difference between two competing teams
Score_diff	Score difference: absolute value of game score difference
Home_game	Home game (dummy variable, 1 = home game, 0 = away game)
Nation_tv	Nationally televised game: game was broadcast by a national television network (e.g., ESPN, TNT, or ABC) (dummy variable, 1 = yes, 0 = not a nationally televised game)
Loss_s	Lost two or more games in a row (dummy variable, 1 = yes, 0 = lost one game)
Win_1	Won one game (dummy variable, 1 = yes, 0 = lost one game)
Win_s	Won two or more games in a row (dummy variable, 1 = yes, 0 = lost one game)

CHAPTER 4

RESULTS AND DISCUSSION

After data screening, a pool of 523 Facebook posts was generated (see Table 4.1). The results of two regression models are displayed in Tables 4.2 and 4.3 The identified predictors together explained 29.8% of the Like behavior and 17.3% of the Share behavior. These coefficients of determination suggest that highlighting information value is a meaningful way for social media managers and team managers to promote online WOM behavior and that other psychological or situational factors are likely to contribute to the variance of online WOM behavior.

In the domain of content provision, content themes impacted both two types of online WOM behavior. Specifically, when compared with CSR, the other five content themes (i.e., team status, pre-game promotion, game highlight, game summary, and off-court promotion) significantly promoted low-strength Like and high-strength Share behavior among fans. Although marketing activity related to CSR has been shown to improve consumer attitude and purchase intention (Creyer & Ross, 1997; Walker & Kent, 2009), few studies have compared its effectiveness and efficiency to other traditional marketing efforts, such as product advertising and sales promotion. As suggested by the results of the current study, marketing efforts related to CSR might boost actual online WOM behavior; however, its influence was weaker than other game-related content or even general off-court promotion.

To further identify differences among the effects of team status, pre-game promotion, game highlight, game summary, and off-court promotion further, regression analyses using different reference groups were conducted. Compared with off-court promotion, team status (B = 5626.124, $p = .035$), game highlight (B = 5831.047, $p < .001$), and game summary (B = 5269.214, $p = .008$) significantly increased Like behavior. Compared with off-court promotion, none of other content themes significantly increased Shared behavior, but it was worth to note that the game summary exerted a relatively strong influence (B = 238.989, $p = .148$). Compared with pre-game promotion, team status (B = 5725.002, $p = .055$), game highlight (B = 5928.095, $p < .001$), and game summary (B = 5370.680, $p = .018$) significantly increased Like behavior. Game highlight (B = 325.793, $p = .022$) and game summary (B = 358.860, $p = .032$) significantly increased Share behavior. No significant difference between off-court promotion and pre-game promotion or among team status, game highlight, and game summary emerged for Like behavior. No significant difference between game highlight and game summary or among team status, off-court promotion, and pre-game promotion emerged for Share behavior. Overall, the basketball-related and non-profit-oriented themes (i.e., game highlight, game summary, and team status) were more likely to stimulate online WOM behavior than non-basketball-related or profit-oriented themes (i.e., CSR, off-court promotion, and pre-game promotion).

Compared with video-based content, image-based content was more likely to promote online WOM behavior, especially low-strength Like behavior (B = 8985.820, $p < .001$). The media usage of sport fans might explain these results: among 1.32 billion Facebook users in 2014, 81.24% used mobile devices to access Facebook, and 30.29% *only* used mobile devices to access Facebook (Hamburger, 2014). Therefore, the convenience of information consumption might lead fans to favor image-based content over video-based content. In addition, the economic cost of data plan and the public social environment may also hold back fans' consumption of video-based content.

The findings showed that consumers engaged more frequently in Like and Share behavior on Monday, especially compared with Tuesday and Wednesday. This finding partially supported Watanabe et al. (2015), who found that time frames impacted fans' social media consumption (i.e., fans used Twitter more frequently on Monday than Sunday). This "Monday effect" might result from the human need for socialization, a need that drives people to seek widely-accepted social proxies (e.g., professional sports) that might help them strengthen group identity or reinforce connections with other stakeholders (e.g., colleagues and friends) after a weekend of relatively lower contact. Compared to November (i.e., the first month of the NBA season), fans were less likely to engage in Like and Share behavior in the second half of the regular season: Month_3 (B_{LIKE} = -3345.784, p = .095; B_{SHARE} = -374.653, p = .018) and Month_4 (B_{LIKE} = -3993.228, p = .066; B_{SHARE} = -301.472, p = .133). That is, both high- and low-strength online WOM behavior were most frequent at the beginning of the NBA season.

Star power of post content did not exert a significant influence on either type of online WOM behavior. One potential reason for this finding is that the effect of star power might be mitigated by the group identity. Based on the social identity theory, people engaged in socialization practices (e.g., evaluation of one's behavior and allocation of resources) tend to have in-group bias, a phenomenon in which in-group elements (e.g., group members and group stereotypes) are favored over out-group elements (Tajfel & Turner, 1979; Taylor & Doria, 1981). On team Facebook pages, most followers identify with a team to a certain degree and, therefore, have an in-group bias toward that team's players. For example, fans might even favor players with lower star power. A second explanation is that players with low star power usually have a smaller chance of being the focus of a post and then probably only after an extraordinary performance compensates for their low star power.

In the domain of game attractiveness, a higher position (i.e., smaller value) in the Forbes Ranking of NBA team valuations significantly promoted both Like (B = -769.029, $p < .001$) and Share (B = -47.973, $p < .001$) behavior, indicating that a team's market, brand, and arena value influenced online WOM behavior. Among three ranking indices, the power ranking of the away team significantly impacted Like (B = 279.185, $p = .001$) and Share (B = 16.080, $p = .009$) behavior, and the power ranking of the home team was negatively linked to Like behavior (B = -198.748, $p = .178$). Together, a higher home team ranking and a lower away team ranking, a combination that is likely to produce a win for the home team, correlated with greater online WOM behavior. In terms of game outcome, winning (either one game or a streak) was more likely to produce online WOM behavior than losing one game. This result confirmed the human need for self-enhancement, according to which people are motivated to increase feelings of personal worth and to advance their social status (Epstein, 1983; Escalas & Bettman, 2003). However, fans were more likely to engage in Share behavior during a losing streak than after losing one game. According to the social identity theory, when one's group identity is threatened by a realistic threat, a symbolic threat, or a group esteem threat (e.g., a losing streak), one is more likely to exhibit stronger in-group bias (Riek, Mania, & Gaertner, 2006; Tajfel & Turner, 1979). Crocker and Luhtanen (1990) further pointed out that people with high collective self-esteem are more likely to exhibit in-group bias. In the current study, fans frequently engaging in Share behavior tended to have high collective self-esteem. Therefore, they exhibited stronger in-group bias (e.g., sharing a post) during a losing streak than after losing one game.

Consistent with previous studies (Zhang et al., 1995; Watanabe et al., 2015), the number of all-stars in a game and being nationally televised significantly impacted both types of online WOM behavior. After controlling for other related variables, such as home team weekly ranking

(r = -.578) and number of all-stars in one game (r = .522), the status of playoff contender did not positively influence online WOM behavior. Another situational variable of game attractiveness, whether a game was home or away, did not significantly influence online WOM behavior, perhaps due to the fact that advancements in media technology have mitigated perceived geographic distance and facilitated media consumption among fans.

Building upon the product value research, this study conceptualized the construct of information value and identified two key environmental antecedents (i.e., content provision and game attractiveness). The findings of this study confirmed the crucial influence of information value on fans' online WOM, providing a new theoretical approach to analyze this phenomenon in the context of sport marketing communications.

The current study provided manipulable references that can help social media managers or team managers increase information value and, in turn, capitalize on the benefits of online WOM. Specifically, in the domain of content provision, gradually increasing the supply of game-related and non-profit-related content (e.g., team status, game summary, and game highlight) and reducing content about the CSR and off-court promotion might be effective. Social media specialists should consider rephrasing post content about off-court promotion and profit-related promotion (e.g., pre-game promotion) to sound more game-related and less commercial. The findings also suggest that increasing content supply on Monday to meet fans' socialization needs could boost online WOM behavior. Social media managers should consider increasing image-based content, especially if this preference is tied to a pursuit of convenience in social media consumption.

In the domain of game attractiveness, the results of this study confirmed the crucial influence of high game quality on game-related consumption, including online WOM behavior.

In the short run, managers should coordinate the supply of information based on specific situations of game attractiveness. For example, increasing content supply might be effective (a) when a game involves more all-star players or is nationally televised and (b) when the home team has an advantage in terms of market size, arena value, or brand value, has a high power ranking, is playing against a strong opponent, wins a game, or is on a losing streak. In the long run, team managers should strive to increase team value in terms of brand value, market size, and arena value, elevate team rankings, recruit more all-star players, generate more wins, and schedule more nationally televised games.

Several limitations of the current study should be acknowledged. First of all, the current study categorized social media content into only six themes. More detailed content analysis is strongly recommended to provide more specific and in-depth information. Second, this study was conducted in the context of an NBA regular season, limiting the generalizability of its findings and conclusions. Therefore, future studies that focus on other sport settings (e.g., other professional leagues, playoffs, or intercollegiate sports) are needed to verify (or challenge) the findings of the current study. Third, like the online community, a team's Facebook page might have a large number of lurkers who always observe rather than actively participate in the public communication (Clavio, 2008; Nonnecke & Preece, 2000). Therefore, for the group of lurkers, the findings of this study might be less effective to engage them in Like and Share behavior. Fourth, Facebook users' socio-demographic information (e.g., gender, age, geographic location, and household income) was not available in this study, which makes the representativeness of the current sample largely unknown. Although the secondary data in a natural setting (i.e., Facebook pages of professional sport teams) might mitigate the potential negative impact, future studies should strive to obtain a comprehensive and representative dataset in the context of social media.

Table 4.1

Summary of Descriptive Statistics for the Selected Variables (N = 523)

	Mean	SD	Max	Min	Frequency*
Cont_star	156.58	164.124	400	10	
CSR	.06	.243	1	0	33
Team_stat	.09	.292	1	0	49
Preg_prom	.14	.347	1	0	73
Game_high	.33	.472	1	0	174
Game_summ	.20	.402	1	0	106
Off_prom	.17	.376	1	0	89
Image	.39	.489	1	0	205
Video	.61	.489	1	0	318
Mon	.17	.373	1	0	87
Tue	.17	.374	1	0	88
Wed	.16	.371	1	0	86
Thu	.12	.324	1	0	62
Fri	.10	.302	1	0	53
Sat	.15	.357	1	0	78
Sun	.13	.339	1	0	69
Month_11	.21	.408	1	0	110
Month_12	.26	.438	1	0	135
Month_3	.27	.444	1	0	139
Month_4	.27	.442	1	0	139
Team_value	10.26	7.367	24	3	
Allstar	2.20	1.093	5	0	
Po_cont	.84	.369	1	0	438
Poff_cont_no	.16	.369	1	0	85
Home_rank	13.89	6.692	30	4	
Away_rank	14.64	8.653	29	1	
Rank_diff	8.89	6.290	25	1	
Score_diff	8.07	5.394	34	2	
Home_game	.58	.494	1	0	303
Away_game	.42	.494	1	0	222
Nation_tv	.14	.351	1	0	75

Nation_tv_no	.86	.351	1	0	448
Loss_1	.22	.412	1	0	113
Loss_s	.17	.376	1	0	89
Win_1	.34	.475	1	0	179
Win_s	.27	.445	1	0	142
Like	6882.28	14741.459	158000	0	
Share	434.61	1142.318	14383	0	

Note: * means categorical variables only

Table 4.2

Estimation Regression Results with MLR Estimator (DV = Like Behavior)

	Coefficients	Robust S.E.	*P*-Value	VIF
Cont_star	3.575	4.237	0.399	1.160
Team_stat	9822.101	3132.186	0.002	2.553
Game_prom	3888.509	1535.536	0.011	3.037
Game_high	10035.243	1874.576	0.000	5.273
Game_summ	9445.484	2312.413	0.000	3.615
Off_prom	4086.001	1605.405	0.011	3.438
Image	8985.820	1933.829	0.000	1.596
Tue	-2862.252	1392.988	0.040	1.959
Wed	-2253.094	1995.830	0.259	2.073
Thu	755.299	3040.225	0.804	1.872
Fri	-676.015	1891.889	0.721	1.744
Sat	1101.373	1872.431	0.556	2.027
Sun	-99.864	1427.150	0.944	1.681
Month_12	-614.286	1653.511	0.710	2.102
Month_3	-3345.784	2004.911	0.095	2.209
Month_4	-3993.228	2174.131	0.066	2.141
Team_value	-769.029	123.084	0.000	1.489
Allstar	4827.595	947.358	0.000	3.207
Po_cont	-7172.583	3090.402	0.020	3.419
Home_rank	-198.748	147.398	0.178	2.342
Away_rank	279.185	84.726	0.001	2.217
Rank_diff	-49.013	96.260	0.611	1.560
Score_diff	79.659	82.169	0.332	1.526
Home_game	1154.359	1158.768	0.319	1.505
Nation_tv	6743.313	2838.068	0.018	1.373
Loss_s	1152.952	1164.074	0.322	1.824
Win_1	4088.327	1781.239	0.022	2.484
Win_s	5263.831	1665.670	0.002	2.297
B_0	-4738.472	3797.393	0.212	

Table 4.3

Estimation Regression Results with MLR Estimator (DV = Share Behavior)

	Coefficients	Robust S.E.	*P*-Value
Cont_star	0.480	0.409	0.241
Team_stat	336.187	135.298	0.013
Game_prom	215.966	105.236	0.040
Game_high	560.667	147.215	0.000
Game_summ	592.306	177.174	0.001
Off_prom	347.847	141.229	0.014
Image	258.725	160.731	0.107
Tue	-244.678	107.749	0.023
Wed	-165.478	146.095	0.257
Thu	-35.234	231.836	0.879
Fri	219.679	273.585	0.422
Sat	-11.738	134.397	0.930
Sun	-73.569	110.893	0.507
Month_12	-184.103	132.786	0.166
Month_3	-374.653	157.724	0.018
Month_4	-301.472	200.483	0.133
Team_value	-47.973	12.318	0.000
Allstar	331.610	84.426	0.000
Po_cont	-410.048	232.452	0.078
Home_rank	-4.878	12.242	0.690
Away_rank	16.080	6.155	0.009
Rank_diff	0.073	8.129	0.993
Score_diff	3.173	6.325	0.616
Home_game	26.178	105.443	0.804
Nation_tv	300.174	226.605	0.185
Loss_s	150.757	91.469	0.099
Win_1	360.695	144.838	0.013
Win_s	459.251	210.212	0.029
B_0	-299.173	289.204	0.301

REFERENCES

Anderson, D. R., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, 103, 411–423.

Armstrong, C. G., Delia, E. B., & Giardina, M. D. (2014). Embracing the Social in Social Media: An Analysis of the Social Media Marketing Strategies of the Los Angeles Kings. *Communication & Sport*, 4(2), 145-165.

Arndt, J. (1967). Role of product-related conversations in the diffusion of a new product. *Journal of Marketing Research, 4*(3), 291-295.

Bauer, H. H., Reichardt, T., Barnes, S. J., & Neumann, M. M. (2005). Driving consumer acceptance of mobile marketing: A theoretical framework and empirical study. *Journal of Electronic Commerce Research, 6*(3), 181.

Bennett, G., Ferreira, M., Lee, J., & Polite, F. (2009). The role of involvement in sports and sport spectatorship in sponsor's brand use: The case of Mountain Dew and action sports sponsorship. *Sport Marketing Quarterly, 18*(1), 14.

Berger, J. (2014). Word of mouth and interpersonal communication: A review and directions for future research. *Journal of Consumer Psychology, 24*(4), 586-607.

Bhat, S., & Reddy, S. K. (1998). Symbolic and functional positioning of brands. *Journal of Consumer Marketing, 15*(1), 32-43.

Bone, P. F. (1995). Word-of-mouth effects on short-term and long-term product judgments. *Journal of Business Research, 32*(3), 213-223.

Boyd, T. C., & Krehbiel, T. C. (1999). The effect of promotion timing on major league baseball attendance. *Sport Marketing Quarterly, 8*(4), 23-34.

Boyd, T. C., & Krehbiel, T. C. (2003). Promotion timing in Major League Baseball and the stacking effects of factors that increase game attractiveness. *Sport Marketing Quarterly, 12*(3).

Brown, T. J., Barry, T. E., Dacin, P. A., & Gunst, R. F. (2005). Spreading the word: Investigating antecedents of consumers' positive word-of-mouth intentions and behaviors in a retailing context. *Journal of the Academy of Marketing Science, 33*(2), 123-138.

Brown, W. O., & Sauer, R. D. (1993). Does the basketball market believe in the hot hand? Comment. *American Economic Review, 83*(5), 1377-1386.

Byon, K. K., Zhang, J. J., & Baker, T. A. (2013). Impact of core and peripheral service quality on consumption behavior of professional team sport spectators as mediated by perceived value. *European Sport Management Quarterly, 13*(2), 232-263.

Byon, K. K., Zhang, J. J., & Connaughton, D. P. (2010). Dimensions of general market demand associated with professional team sports: Development of a scale. *Sport Management Review, 13*(2), 142-157.

Carlson, J., & O'Cass, A. (2010). Exploring the relationships between e-service quality, satisfaction, attitudes and behaviours in content-driven e-service web sites. *Journal of Services Marketing, 24*(2), 112-127.

Creyer, E. H., & Ross, W. T. (1997). Tradeoffs between price and quality: How a value index affects preference formation. *The Journal of Consumer Affairs, 31*(2), 280-302.

Cristobal, E., Flavián, C., & Guinalíu, M. (2007). Perceived e-service quality (PeSQ) Measurement validation and effects on consumer satisfaction and web site loyalty. *Managing Service Quality: An International Journal, 17*(3), 317-340.

Crocker, J., & Luhtanen, R. (1990). Collective self-esteem and ingroup bias. *Journal of Personality and Social Psychology, 58*(1), 60.

Clavio, G. (2008). Demographics and usage profiles of users of college sport message boards. *International Journal of Sport Communication*, 1(4), 434-443.

Clavio, G., & Kian, T. M. (2010). Uses and gratifications of a retired female athlete's Twitter followers. *International Journal of Sport Communication*, 3(4), 485-500.

De Matos, C. A., & Rossi, C. A. V. (2008). Word-of-mouth communications in marketing: A meta-analytic review of the antecedents and moderators. *Journal of the Academy of Marketing Science, 36*(4), 578-596.

Duan, W., Gu, B., & Whinston, A. B. (2008). Do online reviews matter?—An empirical investigation of panel data. *Decision Support Systems, 45*(4), 1007-1016.

Eagleman, A. N. (2013). Acceptance, motivations, and usage of social media as a marketing communications tool amongst employees of sport national governing bodies. *Sport Management Review*, 16(4), 488-497.

Engel, J. F., Kegerreis, R. J., & Blackwell, R. D. (1969). Word-of-mouth communication by the innovator. *Journal of Marketing, 33*(3), 15-19.

Epstein, S. (1983). The unconscious, the preconscious, and the self-concept. In J. Suls & A. G. Greenwald (Eds.), *Psychological perspectives on the self* (Vol. 2, pp. 219-247). Hillsdale, NJ: Erlbaum.

Escalas, J. E., & Bettman, J. R. (2003). You are what they eat: The infulence of reference groups on consumers' connections to brands. *Journal of Consumer Psychology*, *13*(3), 339-348.

Filo, K., Lock, D., & Karg, A. (2015). Sport and social media research: A review. *Sport Management Review*, 18(2), 166-181.

Forbes Corporate Communications. (2016). Forbes Releases 18th Annual NBA Team Valuations. from http://www.forbes.com/sites/forbespr/2016/01/20/forbes-releases-18th-annual-nba-team-valuations/#466236386e3e

Frederick, E. L., Burch, L. M., & Blaszka, M. (2015). A shift in set: Examining the presence of agenda setting on Twitter during the 2012 London Olympics. *Communication & Sport*, 3(3), 312-333.

Geurin, A. N., & Burch, L. M. (2017). User-generated branding via social media: An examination of six running brands. *Sport Management Review*, 20(3), 273-284.

Geurin-Eagleman, A. N., & Burch, L. M. (2016). Communicating via photographs: A gendered analysis of Olympic athletes' visual self-presentation on Instagram. *Sport Management Review*, *19*(2), 133-145.

Godes, D., & Mayzlin, D. (2004). Using online conversations to study word-of-mouth communication. *Marketing Science*, 23(4), 545-560.

Greenwell, T. C., Fink, J. S., & Pastore, D. L. (2002). Assessing the influence of the physical sports facility on customer satisfaction within the context of the service experience. *Sport Management Review*, *5*(2), 129-148.

Gruen, T. W., Osmonbekov, T., & Czaplewski, A. J. (2006). eWOM: The impact of customer-to-customer online know-how exchange on customer value and loyalty. *Journal of Business Research*, *59*(4), 449-456.

Hair, J. F., Black, W., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Upper Saddle River, NJ: Pearson Prentice Hall.

Hambrick, M. E. (2012). Six degrees of information: Using social network analysis to explore the spread of information within sport social networks. *International Journal of Sport Communication*, 5(1), 16-34.

Hambrick, M. E., Simmons, J. M., Greenhalgh, G. P., & Greenwell, T. C. (2010). Understanding professional athletes' use of Twitter: A content analysis of athlete tweets. *International Journal of Sport Communication, 3*(4), 454-471.

Hamburger, E. (2014). Facebook's new stats: 1.32 billion users, 30 percent only use it on their phone. from http://www.theverge.com/2014/7/23/5930743/facebooks-new-stats-1-32-billion-users-per-month-30-percent-only-use-it-on-their-phones

Hartline, M. D., & Jones, K. C. (1996). Employee performance cues in a hotel service environment: Influence on perceived service quality, value, and word-of-mouth intentions. *Journal of Business Research, 35*(3), 207-215.

Harris, M. M., & Schaubroeck, J. (1990). Confirmatory modeling in organizational behavior/human resource management: Issues and applications. *Journal of Management*, *16*(2), 337-360.

Holbrook, M. B. (1994). The nature of consumer value. In R. T. Rust & R. L. Oliver (Eds.), *Service quality: New directions in theory and practice*. Newbury Park, CA: Sage.

Holsti, O. R. (1969). *Content analysis for the social sciences and humanities*. Reading, MA: Addison-Wesley.

James, J. D., Trail, G. L., Zhang, J. J., Wann, D. L., & Funk, D. (2006). *Bringing parsimony to the study of sport consumer motivations: Development of the Big 5.* Paper presented at the Annual conference of North American Society for Sport Management, Kansas City, MO.

Koiso-Kanttila, N. (2004). Digital content marketing: A literature synthesis. *Journal of Marketing Management*, *20*(1-2), 45-65.

Ladhari, R. (2010). Developing e-service quality scales: A literature review. *Journal of Retailing and Consumer Services, 17*(6), 464-477.

Lieb, R. (2011). *Content marketing: Think like a publisher-How to use content to market online and in social media*. Indianapolis, IN: Que Publishing.

Lindlof, T. R., & Taylor, B. C. (2011). *Qualitative communication research methods* (3 ed.). Thousand Oaks, CA: Sage.

Mathews, C., Ambroise, L., & Brignier, J.-M. (2009, May). *Hedonic and symbolic consumption perceived values: Opportunities for innovators and designers in the fields of brand and product design.* Paper presented at the Renaissance & Renewal in Management Studies, Liverpool, United Kingdom.

McKee, D., Simmers, C. S., & Licata, J. (2006). Customer self-efficacy and response to service. *Journal of Service Research, 8*(3), 207-220.

McWilliams, A., Siegel, D. S., & Wright, P. M. (2006). Corporate social responsibility: Strategic implications. *Journal of Management Studies*, 43(1), 1-18.

Min, S. D., Zhang, J. J., Kim, M., & Kim, C. (2014). Understanding consumers of Asian female sports: A case study of the Women's Korean Basketball League. *International Journal of Sport Management and Marketing, 15*(1-2), 19-35.

Montgomery, D. C., Peck, E. A., & Vining, G. G. (2001). *Introduction to linear regression analysis* (3 ed.). New York: Wiley.

Muthen, L. K., & Muthen, B. O. (2012). *Mplus user's guide* (7th ed.). Los Angeles, CA.

Nonnecke, B., & Preece, J. (2000). *Lurker demographics: Counting the silent*. Paper presented at the SIGCHI conference on Human Factors in Computing Systems, Hague, Netherlands.

Park, C. W., Jaworski, B. J., & Maclnnis, D. J. (1986). Strategic brand concept-image management. *Journal of Marketing, 50*(4), 135-145.

Patton, M. Q. (2012). *Qualitative research and evaluation methods* (3 ed.). Thousand Oaks, CA Sage.

Paul, R. J., Wachsman, Y., & Weinbach, A. P. (2011). The Role of Uncertainty of Outcome and Scoring in the Determination of Fan Satisfaction in the NFL. *Journal of Sports Economics,* 12(2), 213-221.

Pedersen, P. M., Miloch, K. S., & Laucella, P. C. (2007). *Strategic sport communication*. Champaign, IL: Human Kinetics.

Pedersen, P. M., & Thibault, L. (2014). *Contemporary sport management* (5 ed.). Champaign, IL: Human Kinetics.

Pfahl, M. E., Kreutzer, A., Maleski, M., Lillibridge, J., & Ryznar, J. (2012). If you build it, will they come?: A case study of digital spaces and brand in the National Basketball Association. *Sport Management Review*, 15(4), 518-537.

Pulizzi, J., & Barrett, N. (2008). *Get content, get customers: How to use content marketing to deliver relevant, valuable, and compelling information that turns prospects into buyers*. Bonita Springs, FL: Voyager media.

Riek, B. M., Mania, E. W., & Gaertner, S. L. (2006). Intergroup threat and outgroup attitudes: A meta-analytic review. *Personality and Social Psychology Review, 10*(4), 336-353.

Rowley, J. (2008). Understanding digital content marketing. *Journal of Marketing Management, 24*(5-6), 517-540.

Rubin, R. B., Rubin, A. M., & Haridakis, P. M. (1993). *Communication research: Strategies and sources* (3 ed.). Belmont, CA: Wadsworth.

Salaga, S., & Tainsky, S. (2015). The effects of outcome uncertainty, scoring, and pregame expectations on Nielsen ratings for Bowl Championship Series games. *Journal of Sports Economics, 16*(5), 439-459.

Schofield, J. A. (1983). Performance and attendance at professional team sports. *Journal of Sport Behavior, 6*(4), 196.

Scott, O. K. M., Hill, B., & Zakus, D. H. (2012). When the home team is not featured: Comparison of two television network commentaries during broadcasts of the 2006 FIFA World Football Cup. *Sport Management Review, 15*(1), 23-32.

Sears, D. O., & Freedman, J. L. (1967). Selective exposure to information: A critical review. *Public Opinion Quarterly, 31*(2), 194-213.

Shreffler, M. B., & Ross, S. D. (2013). The word-of-mouth phenomenon: Its presence and impact in a sport setting. *International Journal of Sport Communication*, 6(1), 1-18.

Smith, J. B., & Colgate, M. (2007). Customer value creation: A practical framework. *Journal of Marketing Theory and Practice, 15*(1), 7-23.

Statista. (2014). Average number of Facebook friends of users in the United States as of February 2014. from https://www.statista.com/statistics/232499/americans-who-use-social-networking-sites-several-times-per-day

Statista. (2014). Social media usage to follow sports 2014. from https://www.statista.com/statistics/305655/social-media-usage-to-follow-sports

Strauss, A., & Corbin, J. (1990). *Basics of qualitative research*. Newbury Park, CA: Sage.

Swanson, S. R., Gwinner, K., Larson, B. V., & Janda, S. (2003). Motivations of college student game attendance and word-of-mouth behavior: The impact of gender differences. *Sport Marketing Quarterly, 12*(3).

Szymanski, D. M., & Hise, R. T. (2000). E-satisfaction: An initial examination. *Journal of Retailing, 76*(3), 309-322.

Tainsky, S. (2009). Television broadcast demand for National Football League contests. *Journal of Sports Economics, 11*(6), 629-640.

Tainsky, S., Kerwin, S., Xu, J., & Zhou, Y. (2014). Will the real fans please remain seated? Gender and television ratings for pre-game and game broadcasts. *Sport Management Review*, 17(2), 190-204.

Tainsky, S., & McEvoy, C. D. (2012). Television broadcast demand in markets without local teams. *Journal of Sports Economics*, *13*(3), 250-265.

Tainsky, S., Salaga, S., & Santos, C. A. (2013). Determinants of pay-per-view broadcast viewership in sports: The case of the Ultimate Fighting Championship. *Journal of Sport Management*, *27*(1), 43-58.

Tainsky, S., Xu, J., & Zhou, Y. (2014). Qualifying the game uncertainty effect a game-level analysis of NFL postseason broadcast ratings. *Journal of Sports Economics, 15*(3), 219-236.

Tajfel, H., & Turner, J. C. (1979). An integrative theory of intergroup conflict. *Social Psychology of Intergroup Relations, 33*(47), 74.

Taylor, D. M., & Doria, J. R. (1981). Self-serving and group-serving bias in attribution. *Journal of Social Psychology, 113*(2), 201-211.

Tomarken, A. J., & Waller, N. G. (2005). Structural equation modeling: Strengths, limitations, and misconceptions. *Annual Review of Clinical Psychology, 1*, 31-65.

Trusov, M., Bucklin, R. E., & Pauwels, K. (2009). Effects of word-of-mouth versus traditional marketing: Findings from an internet social networking site. *Journal of Marketing*, *73*(5), 90-102.

Villanueva, J., Yoo, S., & Hanssens, D. M. (2008). The impact of marketing-induced versus word-of-mouth customer acquisition on customer equity growth. *Journal of Marketing Research, 45*(1), 48-59.

Walker, M., & Kent, A. (2009). Do fans care? Assessing the influence of corporate social responsibility on consumer attitudes in the sport industry. *Journal of Sport Management, 23*(6), 743.

Wallace, L., Wilson, J., & Miloch, K. (2011). Sporting Facebook: A content analysis of NCAA organizational sport pages and Big 12 conference athletic department pages. *International Journal of Sport Communication, 4*(4), 422-444.

Watanabe, N. M. (2012). Demand for pay-per-view consumption of Ultimate Fighting Championship events. *International Journal of Sport Management and Marketing, 11*(3-4), 225-238.

Watanabe, N. M., Yan, G., & Soebbing, B. P. (2015). Major league baseball and Twitter usage: The economics of social media use. *Journal of Sport Management, 29*(6), 619-632.

Watanabe, N. M., Yan, G., & Soebbing, B. P. (2016). Consumer Interest in Major League Baseball: An Analytical Modeling of Twitter. *Journal of Sport Management, 30*(2), 207-220.

Waters, R. D., Burke, K. A., Jackson, Z. H., & Buning, J. D. (2011). Using stewardship to cultivate fandom online: Comparing how National Football League teams use their web sites and Facebook to engage their fans. *International Journal of Sport Communication*, 4(2), 163-177.

Weston, R., & Gore, P. A. (2006). A brief guide to structural equation modeling. *The Counseling Psychologist*, *34*(5), 719-751.

Westbrook, R. A. (1987). Product/consumption-based affective responses and postpurchase processes. *Journal of Marketing Research*, 258-270.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: Journal of the Econometric Society*, 817-838.

Williams, J., & Chinn, S. J. (2010). Meeting relationship-marketing goals through social media: A conceptual model for sport marketers. *International Journal of Sport Communication*, 3(4), 422-437.

Yang, J., & Leskovec, J. (2010). *Modeling information diffusion in implicit networks*. Paper presented at the 2010 IEEE International Conference on Data Mining, Sydney, Australia.

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *Journal of Marketing*, *52*(3), 2-22.

Zhang, J. J., Lam, E. T., & Connaughton, D. P. (2003). General market demand variables associated with pofessional sport consumption. *International Journal of Sports Marketing & Sponsorship*, *5*(1), 33.

Zhang, J. J., Pease, D. G., Hui, S. C., & Michaud, T. J. (1995). Variables affecting the market competitors on the attendance of professional sport games: The case of a minor league hockey team. *Sport Marketing Quarterly*, *6*(3), 34-40.

Zhou, Z., Bandari, R., Kong, J., Qian, H., & Roychowdhury, V. (2010, July 25). *Information resonance on Twitter: Watching Iran*. SOMA 2010, Washington, DC.