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# The Retweet as a Function of Electronic Word-of-Mouth Marketing: A Study of Athlete Endorsement Activity on Twitter

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The purpose of this study was to examine endorsement-related tweets from athletes and determine which characteristics of those tweets could increase the degree of electronic word-of-mouth marketing (eWOM) generated by the message. Previous literature has suggested that the retweet function in Twitter is a form of eWOM. Through the lens of eWOM, the concepts of vividness, interactivity, and congruence are used to understand what tweet characteristics generate the most retweets. A sample of professional-athlete endorsement and sponsored tweets (*n* = 669) was used and coded based on frameworks adapted from previous studies. Results indicated that the interaction between levels of high vividness and high interactivity generated the highest frequency of retweets. Reported findings could inform athletes and/or brand managers in ways to increase the eWOM of sponsored messages on Twitter.

***Keywords****:* electronic word-of-mouth marketing, interactivity, vividness

For most of the 20th century, brands and organizations have used celebrities as vehicles to advertise and promote products. Currently, one popular method of capitalizing on celebrity status is the use of professional athletes to endorse both sport-related and non-sport-related brands. In 2015, professional athletes were projected to earn an estimated $836 million in endorsement-related projects (McCarthy, 2015). For many athletes, endorsement revenue can exceed contracts or prize money earned while playing; for example, in 2015 Caroline Wozniacki earned approximately $1.8 million in prize money as a professional tennis player but received an estimated $11 million in endorsements ("The World's Highest-Paid," 2016; Weber, 2015).

Previously, endorsement campaigns leveraged traditional media channels (e.g., television or print) to activate the link between brand and athlete. However, as the world becomes more interconnected, marketers and brands are looking toward novel approaches for endorsement activation strategies that directly engage consumers. Specifically, brands are beginning to increase social-media-marketing budgets

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(Heine, 2015) in recognition of a shift toward an increasingly saturated consumer-generated media market (Kapitan & Silvera, 2016). Social-media marketing allows brands and athletes to connect with broader markets at lower costs, and the effort required from the athlete to participate in the campaign is less than traditional advertisements (Heitner, 2015). Individually, several athletes have the social-media presence to attract deals worth thousands of dollars per mention (Weber, 2015). For example, in 2015, a report from Opendorse.com estimated that athletes such as Roger Federer or Maria Sharapova could receive payment in excess of $9,000 for a tweet containing endorsement-related content (Weber, 2015).

As a popular social-media platform for user-generated content and interaction, Twitter claims to maintain 320 million active monthly users of whom 80% access the platform through mobile devices ("Twitter Usage," 2016). As athletes' social-media use matures and access to consumers continues to increase, brands and marketers are increasingly exploring opportunities to increase reach and exposure through social media. Despite claims of reported earnings for promotional content (Weber, 2015), there is still a lack of understanding about social-media marketing and best practices for measuring outcomes. However, work outside of sport indicates that examining the use of the retweet function in Twitter, as a form of electronic word-of-mouth (eWOM) marketing, can provide a relevant measure of message exposure (Hoffman & Fodor, 2010). Thus, the purpose of this study was to examine differences in how often Twitter posts of athlete endorsers are retweeted, based on the characteristics of the message.

# Literature Review

Previous studies have reported the benefits of leveraging the image of celebrity athletes as brand or product endorsers (Lee & Koo, 2015). Athlete endorsement activity continues to grow from year to year because celebrity-athlete endorsement campaigns can penetrate saturated media markets (Charbonneau & Garland, 2005; Kunalic, 2016; Ohanian, 1990). To effectively market athlete–brand relationships, many endorsement campaigns now include activation through the athlete's social-media channels. It appears that brands are receiving some return on this leveraging strategy, as Kunalic noted that 40% of Twitter users admitted they have made a purchase influenced by a tweet from an influencer—in many cases, a famous athlete.

## Twitter and Sport

The growth of Twitter is partially attributed to its early adoption and widespread use by sports organizations and athletes, as well as the interactive nature that permeates the platform (Fisher, 2009; Frederick, Lim, Clavio, & Walsh, 2012; Hambrick & Mahoney, 2011). Described as a microblogging service (Clavio & Kian, 2010), Twitter thrives as an unobstructed avenue of communication (Hambrick & Mahoney, 2011; Pegoraro, 2010). This unobstructed nature fosters the building and maintaining of relationships; thus, sport entities have adopted the platform to communicate more directly with potential and current fans (Browning & Sanderson, 2012; Kassing & Sanderson, 2010; Sanderson, 2010).

As research has moved from investigating Web 1.0 to Web 2.0 technologies, methodologies have adapted to measure motives of social-media users. Clavio and Kian (2010) generated three factors of follower motivation: organic fandom, functional fandom, and interaction. They noted that fans placed in the functional fandom category were motivated by purchase intention of products and other business-related interest. However, Frederick et al. (2012) reported that increases in interactivity—meeting the interactive motivation described by Clavio and Kian—could be a tool for athletes to increase sponsor awareness.

Past research on Twitter in sport has also concentrated on the development of thematic content categories of professional athlete tweets. Hambrick and Mahoney (2011), using the work of Seo and Green (2008) and Clavio (2008), developed six categories of athlete-produced content on Twitter. In addition, Hull (2014), calling on parasocial interaction and self-presentation theory (Goffman, 1959), developed six similar themes. Relevant themes developed from these studies include interactivity, promotional content, fanship, and diversion. Results indicated that, on average, promotional content accounted for roughly 10% of an athlete's tweets. However, scholars tend to agree that Twitter is underutilized as a promotional tool (Hambrick & Mahoney, 2011; Hull, 2014).

## Information Diffusion

As a social-media platform, Twitter allows users to engage with content through functions that represent various levels of engagement and response. Currently, Twitter users have the ability to retweet, favorite ("like"), or comment on messages constructed and posted by other users. While each function may represent various marketing outcomes, recently the primary focus of marketers and academics is the ability of users to diffuse information or content through a retweet (Kim, Sung, & Kang, 2014). The intent behind a retweet is the intentional sharing and spreading of content created by others (Vargo, 2014). However, while a like (favorite) may unintentionally diffuse a message to a degree, the user's primary intent is to provide a positive affirmation to the user posting the message (Vargo, 2014).

Although it is one of the original functions of Twitter, the retweet has received little attention in the sport communication literature. Suh, Hon, and Pirolli, and Chi (2010) describe the retweet as "the key mechanism for information diffusion" (p. 177). The process of diffusing information across networks is often regarded as a manner in which people can share and possibly influence opinions (Bakshy, Hofman, Mason, & Watts, 2011; Rogers-Pettie & Herrmann, 2015). In addition, marketing and digital-media researchers have acknowledged that Twitter is well suited for information diffusion based on message characteristics (e.g., posts containing 140 characters or fewer). However, the retweet does more than just spread a message—it is also considered an indicator of eWOM marketing (Hoffman & Fodor, 2010). The origins of eWOM are traced to the more traditional framework word-of-mouth (WOM) marketing. WOM is used to describe the influence of consumer-to-consumer communication of brand information that can influence consumer opinion (Kozinets, de Valck, Wojnicki, & Wilner, 2010). The impact of WOM marketing is described as a primary source of brand or product information (Godes & Mayzlin, 2004) and can influence consumer prepurchase attitudes (Kimmel & Kitchen, 2014; Lim & Chung, 2011).

However, in response to technological advances, the construct of WOM marketing has evolved to include communications that take place through an electronic medium, conceptualized as electronic word-of-mouth (eWOM) marketing. Scholars operationally define eWOM as any statement made by potential or current consumers about a product through an online medium (Chu & Kim, 2011). Using the concept of eWOM, Kim et al. (2014) reported that individuals who retweeted a brand's messages had higher usage frequency, stronger brand identification, and greater trust toward that brand. In addition, through the lens of eWOM, a retweeted message is seen as a form of user investment (Hoffman & Fodor, 2010) and perceived as more trustworthy by other users (Tavakolifard, Almeroth, & Gulla, 2013). Establishing a link between eWOM, user perceptions, and retweets give marketers a metric to track potential marketing outcomes (Kim et al., 2014). In addition, predictive models suggest that the presence of certain message characteristics (e.g., hyperlinks or a visual component) most often accompany frequently retweeted messages (Alboqami et al., 2015).

# Conceptual Framework

The purpose of this study was to determine whether the number of retweets an athlete's endorsement-related Twitter posts generates differs based on four salient message characteristics. The important constructs identified in the literature, which compose the conceptual framework for the study, were vividness, interactivity, athlete–brand congruence, and gender. In the previous marketing literature, levels of message interactivity and vividness were used to measure fan response to brand messages posted to social media (de Vries, Gensler, & Leeflang, 2012). However, while athlete–brand congruence and gender have been used in previous endorsement literature (Cunningham & Bright, 2012b; Ohanian, 1991), there is a lack of sport literature exploring the impact that other salient message characteristics have on fan response. Descriptions of the four constructs used to classify the messages, and the impact each has on user response to endorsement activity, are outlined following.

## Interactivity

Interactivity is defined as a continuum of interaction between consumer and brand that ranges from no interaction to full interactive communication between two parties (Chua & Bannerjee, 2015). Acknowledging that interactivity operates on a continuum, evidence suggests that consumer response varies based on the degree of interactivity contained in a social-media post (de Vries et al., 2012). To address user response to different levels of interactivity, researchers developed a framework to classify interactivity. de Vries et al. theorized that a highly interactive medium (e.g., Facebook) allows for various levels of interactivity; therefore, a framework was constructed to describe four levels of interactivity. In addition, extant social-media literature reports that low interactivity contains a simple text post that does not require a follower response (Chua & Bannerjee, 2015). However, elements defined as medium or high interactivity elicit greater follower response and are shown to increase social-media metrics (i.e., likes or comments; Chua & Bannerjee, 2015; de Vries et al., 2012). These studies also reported that content coded as medium interactivity did elicit the highest rate of user response. Based on previous literature, we proposed the following hypothesis:

**H1**: Tweets coded as medium interactivity would have a higher frequency of retweets than tweets coded as having high or low interactivity.

## Vividness

Twitter allows users to increase the vividness of a post by including photographs or videos that can range from a couple of seconds to several minutes in length. In relation to message outcomes, the level of vividness has been reported to affect attitudes and message salience (Luarn, Lin, & Chiu, 2015); however, this impact can be mitigated based on the level or degree of vividness used (de Vries et al., 2012). For example, de Vries et al. found that the number of likes a post received (on Facebook) was not affected by the addition of pictures. In addition, they recommend the posting of highly vivid content to generate more Facebook likes. Finally, Luarn et al. reported that the most salient indicator of likes for a Facebook post was content containing highly vivid posts.

The vividness contained in a social-media post is the degree to which the post stimulates the senses of a reader (de Vries et al., 2012). Earlier examinations of vividness in communication literature define the concept based on the breadth and depth of a message (Fortin & Dholakia, 2005; Steuer, 1992). In addition, previous authors linked the breadth of a message to the sensory stimulation achieved by the content. The depth of a message is used to describe the perceived quality of the stimulation (Daft & Lengel, 1986; Fortin & Dholakia, 2005; Steuer, 1992). Because of previous literature and findings, we constructed the following hypothesis:

**H2**: Tweets coded as having high vividness would have a higher frequency of retweets than tweets coded as medium or low vividness.

## The Match-Up Hypothesis

Extant literature examining the fit between celebrity endorsers and brands, commonly referred to as congruence, is often investigated in the context of the match-up hypothesis (Lee & Koo, 2015; Ohanian, 1991). Adopting literature from marketing and advertising, several sport scholars have used this framework to explain consumer response to celebrity-athlete endorsement campaigns (Cunningham & Bright, 2012a; Lee & Koo, 2015). Lee and Koo found that by pairing high credibility and high congruence, fan responses are more positive concerning attitude toward brand and advertisement. In addition, Cunningham and Bright (2012b) reported that female followers and fans were more inclined to trust product endorsements when source credibility and congruence were high. As such, we constructed the following hypothesis:

**H3**: Tweets possessing high congruence between athlete and brand would generate a higher retweet frequency than tweets containing a low congruence.

## Gender

Previous studies have also examined differences in endorsement activity or success based on gender. Female athletes have been found to be more cognizant of sponsor relationships than male athletes are (Cunningham & Bright, 2012a), and female athletes prefer to participate in campaigns that highlight their athletic prowess (Fink, Kane, & LaVoi, 2014). On the other hand, male endorsers have been perceived (by consumers) as being more trustworthy and having greater expertise concerning sport-related products (Boyd & Shank, 2004). Since the process by which a follower retweets a message from an athlete seems to align more with the studies that found male endorsers to be more effective, the following hypothesis was tested:

> **H4**: Tweets from male athletes would be retweeted more often than those from female athletes.

# Methods

## Sample

Data were collected from 16 professional (8 male and 8 female) athletes' Twitter feeds (see Table 1). Initial athlete selection was determined from a list of top earning athletes provided by Forbes.com ("The World's Highest-Paid," 2015). The list provided by Forbes includes athlete income from sources such as winnings, endorsements, and salary. However, due to earning discrepancies between male and female athletes, only two female athletes were present in the top-100 earners for the year. Therefore, a secondary list posted exclusively for top-earning female athletes was used (Badenhausen, 2015). Furthermore, an article posted by Kunalic (2015) included a more substantial estimation of endorsement earnings, therefore providing

**Table 1 Athlete Twitter Feed Sample**

| Athlete | Sport | Tweets |
|---|---|---|
| Ana Ivanovic | Tennis | 162 |
| Caroline Wozniacki | Tennis | 183 |
| Danica Patrick | NASCAR | 202 |
| Kevin Durant | NBA | 80 |
| Kobe Bryant | NBA | 205 |
| Lebron James | NBA | 129 |
| Maria Sharapova | Tennis | 115 |
| Novak Djokovic | Tennis | 215 |
| Petra Nemcova | Tennis | 200 |
| Roger Federer | Tennis | 210 |
| Ronda Rousey | Mixed martial arts | 217 |
| Rory Mcilroy | Golf | 101 |
| Serena Williams | Tennis | 237 |
| Stacy Lewis | Golf | 198 |
| Tiger Woods | Golf | 204 |
| Usain Bolt | Track & field | 229 |

further support for the method of athlete selection (Weber, 2015). Athletes (male or female) were removed from the sample if they did not have a verified Twitter profile, did not tweet in English, or, after a cursory examination, only promoted their personally owned/controlled brands.

## Data Collection

Data were collected using the data-scraping and text-analytics program DiscoverText. DiscoverText connects to Twitter through an application program interface (API) to mine data (e.g., tweets, user profile information, comments) directly from the social-media platform. In addition, DiscoverText provides the ability to customize and code large data sets from preselected Twitter feeds through scheduled fetches (Blaszka, Burch, Frederick, Clavio, & Walsh, 2012). After the final confirmation of the sample, two scheduled fetches were implemented, August 17–22, 2015, and February 15–22, 2016, to obtain the total sample of $N = 2{,}897$ tweets.

Once data were collected, a content analysis through a two-step deductive coding schema was implemented to categorize tweets based on concepts from the literature (Flick, 2014). Content analysis is a flexible text-analytics tool that allows researchers to explore patterns that emerge from a data set (Blaszka et al., 2012; Hsieh & Shannon, 2005). Content analysis was previously used in sport communication literature to highlight the use of athlete or sport-organization use of Twitter (Gibbs, O'Reilly, & Brunette, 2014; Pegoraro, 2010). Stage 1 of coding involved separating endorsement messages (promotional content) and messages containing sponsor impressions (Quester & Farrelly, 1998) from other established content themes, based on a modified form of Hull's (2014) promotional schema. Stage 2 of coding required categorizing promotional content into the concepts of vividness and interaction modified from de Vries et al. (2012) and congruence (Lee & Koo, 2015). The original construct reported by de Vries et al. contained four levels of vividness and four levels of interaction. However, due to the fundamental differences between Twitter and Facebook—the platform studied by de Vries et al.—we modified the coding framework to include three levels of vividness and three levels of interactivity.

In addition, stage 2 of coding differentiated the two levels of sponsor and athlete congruence. For this study, the construct was coded as a dichotomous variable of either high or low sponsor–athlete congruence. Previous studies (Lee & Koo, 2015) have considered this an appropriate measure of the fit between sponsor and athlete. Table 2 has a more detailed description of the criteria at each stage of coding.

## Analysis

A $2 \times 3 \times 3 \times 2$ analysis of variance (ANOVA) was conducted in SPSS 23.0 to examine main effects and two-way interactions using Type 3 sums of squares. The dependent variable, representing information diffusion, was the total number of retweets reported for every individual endorsement tweet. The number of favorites a tweet received, which is often measured in conjunction with retweets, was excluded from this study because it is considered a lower level of user engagement and does not readily function as a vehicle for information diffusion (Meenaghan, 2013). The independent variables were gender, vividness, interactivity, and congruence. Initially, we intended to use the athlete's number of followers (when the tweet was

**Table 2 Coding Description for Dependent Variables**

| | Promotional Content Characteristics | |
|---|---|---|
| **Variable** | **Level** | **Operational definition** |
| Stage 1 | | |
| the promoter (Hull, 2014) | | When an athlete would discuss or post impressions of one of his or her sponsors or endorsement deals. |
| Stage 2 | | |
| vividness | Low | Content contains no graphical material. |
| | Medium | Content contains a pictorial representation of sponsor (e.g., logo on clothing, watermark, etc.) or some form of auditory playback. |
| | High | Content contains a video with the sponsor represented or stimulated more than just the sense of sight. |
| interactivity | Low | No form of interaction. |
| | Medium | Call to action, contest, voting. |
| | High | Athlete originated a quiz, asked a question, or hosted a sponsored question-and-answer session. |
| congruence | Low | Sponsor was not directly related to the athlete's sport. |
| | High | Sponsor was directly related to the ahlete's sport. |

*Note*. The original conceptual framework supplied by de Vries et al. (2012) allowed content to be coded into multiple interactive and vividness categories. We determined that, due to the brevity of Twitter content, the categories used here should be mutually exclusive.

posted) as a covariate, as previous works have suggested a positive relationship between numbers of followers and retweets generated (Suh et al., 2010). However, the covariate was removed from the model due to seemingly gross violations of the homogeneity-of-regression assumption on interactivity and vividness. In addition, the removal of the covariate did not affect statistical significance.

When testing ANOVA assumptions, the continuous dependent variable exhibited a grossly nonnormal distribution (extremely positively skewed and leptokurtic); thus, a logarithmic transformation was performed (Stevens, 2009). Levene's test was significant, likely due to the relatively large sample size and the conservative nature of Levene's test, but there did not appear to be any other problematic assumption violations. Finally, outlier checks were performed using *z*-score transformations—30 data points fell outside of a 2-*SD* range and were removed from the sample.

# Results

## Descriptive Statistics

From the original sample of $N = 2{,}897$ tweets, a total of $n = 669$ tweets were coded as a promotional activity during Stage 1. The final number of promotional tweets retained for analysis, after the removal of outliers, was $n = 639$. The athlete with the highest percentage of sponsor tweets was Kevin Durant with 41 (51%) out of 80 total tweets, and the lowest reported total was Ana Ivanovic with 14 (8%) out of 162 tweets. The average number of retweets on this subsample was $M$ = 331.9 ($SD$ = 488.18). For the construct of vividness, tweets coded as medium vividness had the largest group size ($n$ = 353), and high vividness had the lowest group size ($n$ = 70). The largest group on the level of interactivity was medium ($n$ = 340), and high interactivity was the smallest group ($n$ = 97).

## Main Effects and Interaction Effects

Results of the modified factorial ANOVA (main effects and two-way interactions only) indicated that the omnibus model showed significant group differences on the number of retweets, $F(16, 639) = 24.216, p < .001, \eta_p^2 = .384$. All tests were evaluated with an alpha value of .05. All main effects and interactions are reported in Table 3.

A Bonferroni post hoc test was used to examine pairwise differences between the levels of vividness and interactivity. Pairwise comparisons for the three levels of vividness yielded significant differences ($p < .001$) between high vividness ($M$ = 189.43) and low vividness ($M$ = 77.17) and between high ($M$ = 189.43) and medium vividness ($M$ = 88.49; $p$ = .011). In addition, there was a significant difference in means between medium vividness ($M$ = 88.49) and low vividness ($M$ = 77.17; $p$ = .002). Significant differences were also observed between medium interactivity ($M$ = 152.93) and high interactivity ($M$ = 84.02; $p$ = .011), as well as medium interactivity ($M$ = 152.93) and low levels of interactivity ($M$ = 100.69; $p$ = .002). Finally, there was a significant difference between high ($M$ = 84.02) and low levels of interactivity ($M$ = 100.69; $p < .001$).

All possible two-way interaction effects from the full factorial model were also examined. Of the six two-way interactions, Gender × Interactivity ($p$ = .213) and Gender × Congruence ($p$ = .954) were the only interactions that were not sig-

**Table 3 Analysis of Variance (ANOVA) Results**

| | *df* | *F* | *p* | $\eta_p^2$ |
|---|---|---|---|---|
| Corrected model | 16 | 24.22 | <.001* | .384 |
| Vividness | 2 | 9.69 | <.001* | .030 |
| Interactivity | 2 | 8.19 | <.001* | .026 |
| Congruence | 1 | 23.48 | <.001* | .036 |
| Gender | 1 | 54.36 | <.001* | .084 |
| Vividness × Interactivity | 4 | 3.721 | .005* | .023 |
| Vivid × Congruence | 2 | 3.01 | .05* | .01 |
| Vivid × Gender | 2 | 4.58 | .011* | .015 |
| Interactivity × Congruence | 2 | 5.15 | .006* | .016 |
| Interactivity × Gender | 2 | 1.55 | .213 | .005 |
| Gender × Congruence | 1 | 0.003 | .954 | .00 |

*$\alpha$ = .05.

nificant. The four remaining interactions were Vividness × Interactivity ($p$ = .005), Vividness × Congruence ($p$ = .05), Vividness × Gender ($p$ = .011), and Interactivity × Congruence ($p$ = .006) and were all significant. Significant interaction effects can be found in Figure 1.

# Discussion

## Theoretical and Practical Implications

Previous studies have examined the effectiveness of partnerships between celebrity athletes and brands to promote products and also highlighted numerous aspects of Twitter use among fans and athletes (Hull, 2014; Lee & Koo, 2015). However, the findings of this study reveal several facets of athlete Twitter activity and fan response through message diffusion based on tweet characteristics. By identifying common features of promotional or sponsored content, this study attempted to measure retweet frequency as an eWOM outcome. Of the four proposed hypotheses, all were either partially or fully supported; however, the findings suggest that brands and athletes need to consider the complexity of Twitter-message construction when planning promotional content.

The findings of this study revealed that a significant interaction effect does exist between levels of interactivity and vividness. The interaction that produced the highest number of retweets involved tweets containing high interactivity and high vividness characteristics. While this finding partially supports previous research stating that increases in levels of vividness are positively related to social-media metrics/outcomes (de Vries et al., 2012; Luarn et al., 2015), it does not support previous results concerning levels of interactivity. Chua and Bannerjee (2015) reported that when social-media posts contained high levels of interactivity, there was a decrease in reported social-media metrics. However, the lack of support may be partially explained by previous studies' not considering the potential impact of interaction effects, and those analyses were conducted using Facebook instead of Twitter (de Vries et al., 2012; Luarn et al., 2015), which are markedly different platforms. These results need to be viewed with some caution, however, as the high-interactivity cell size was quite small compared with the other levels. That being said, this result may indicate to practitioners that followers might be more likely to diffuse endorsement content that contains videos and are perceived to prompt individualized interaction between athlete and follower.

Furthermore, messages coded as high interactivity and low vividness had the lowest number of retweets. The low eWOM activity produced by these messages may be due in part to the exact nature of the interactions. Many of the items coded at this level were sponsored question-and-answer sessions between athletes and followers. Since this content was more conversational between the athlete and a single follower, it seems unlikely that these messages would often be retweeted, if at all. From a practical standpoint, when constructing a sponsored or promotional message parties should concentration on interacting with as many followers as possible while producing content that stimulates at least a single sense. However, if high interactivity and eWOM are the primary goals of an endorsement campaign, then highly vivid content (e.g., videos) should be considered during the construction of a sponsored message.

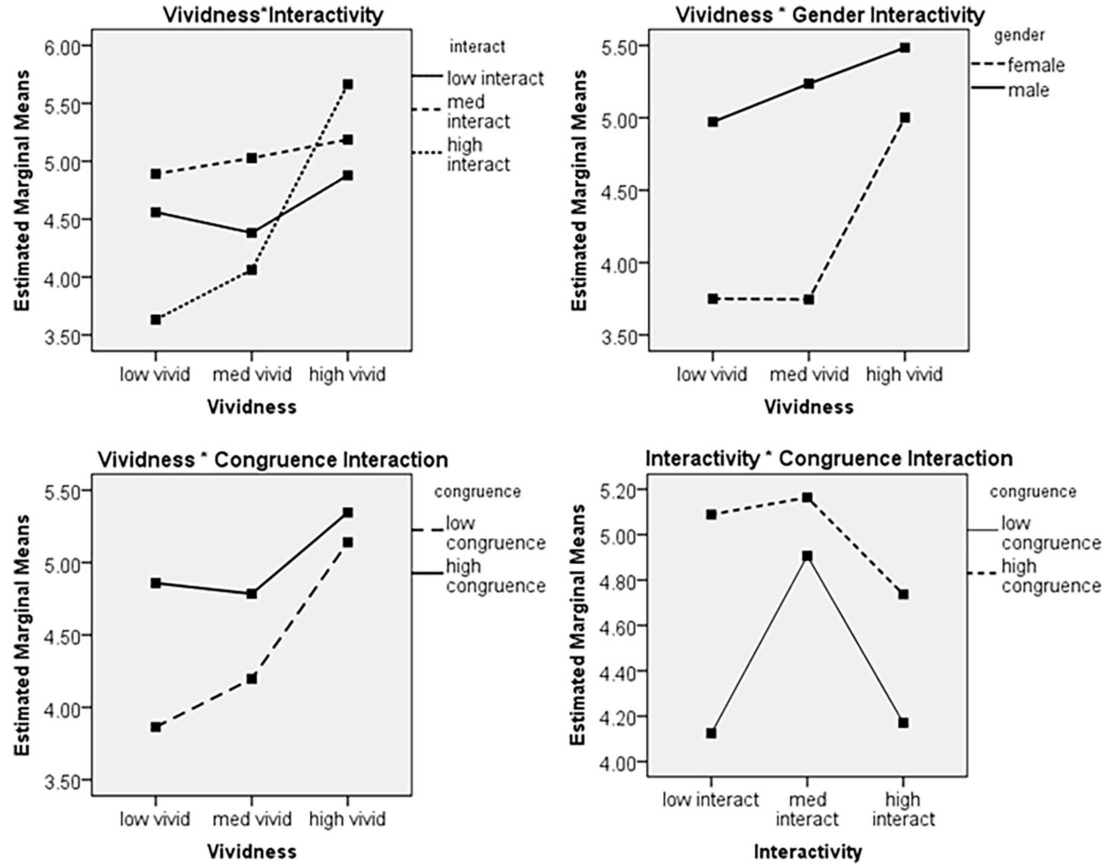


**Figure 1** — Significant interaction effects from the 2 × 3 × 3 × 2 analysis of variance. Interactions include (top left to bottom right) Vividness × Interactivity, Vividness × Gender, Vividness × Congruence, and Interactivity × Congruence. *Note*. med = medium.

The second significant interaction effect occurred between congruence and interactivity. Results indicated that when interactivity was high or low, low brand–athlete congruence does potentially limit the propagation of a message. This finding may be due to a lack of perceived trust toward low congruence of athlete–brand match, as well as between follower and message originator, that is needed for a user to want to retweet a message (Cunningham and Bright, 2012b; Kim et al., 2014). In addition, it is possible that fans are more sensitive to congruence when interactivity is low or high. However, medium interactivity seems to mediate the impact of congruence. In other words, fans seem to be less sensitive to congruence when athletes use a call to action (e.g., hyperlink) or a hashtag in promotional messages. Based on the reported findings, social-media strategy for incongruent brand–athlete matches should focus on messages that include contests, calls to action, or other characteristics that relate to medium interactivity (although it should be noted that this approach should only be considered if high levels of eWOM are the goal). For example, Kevin Durant, promoting the sponsor Sparkling Ice through a contest, tweeted "You can still get a chance to score on me w/my partner @SparklingICE - Head to [link and image removed] for your shot." This message appeared to be particularly effective at generating eWOM as it was retweeted 758 times, which was over 3 times more than average ($M$ = 251.5 retweets) from the original sample.

Similarly, the significant interaction between vividness and congruence would imply that the difference in retweets can be mitigated by using highly vivid content in cases where congruence between brand and athlete is low. In practical terms, when the athlete and brand are perceived as a low-congruent match, the campaign should focus on using messages that stimulate multiple senses (e.g., videos, .gifs, or vines). An example of this strategy would be Serena Williams tweeting "Download the song in my @Chase commercial for free for a ltd time & quantity: [link and video removed] #MasterTheOpen." Despite a lack of an obvious link between the brand of Chase Bank and Serena Williams, this post was retweeted 694 times. Although three-way interactions were beyond the scope of this study, it is interesting to note that this message also exhibited a medium level of interactivity (i.e., a call to action, in this case a song download).

The final significant interaction was observed between gender and vividness. Main effects reported a significant difference in gender, with male athletes generating higher frequencies of retweets. The significant finding regarding gender differences should be viewed with caution, however, as numbers of followers can affect retweet frequency (Suh et al., 2010). A follow-up independent $t$ test (not shown) indicated that, as a group, the male athletes had significantly more followers than the female athletes. Despite significant gender differences, the interaction effect revealed that female athletes could decrease eWOM outcome differences when constructing messages that contain highly vivid content. However, it should be noted that female athletes only produced 21 tweets that were coded as highly vivid. Of those 21 tweets, 13 were produced by Serena Williams (approximately 5,105,569 followers) and Maria Sharapova (approximately 1,848,291 followers). Each athlete accounted for roughly 58% of total followers for the female portion of the sample. Thus, this significant interaction could be partially driven by the high number of followers of these two athletes.

## Limitations and Future Research

Using the data-scraping tool DiscoverText (and consequently Twitter API) was a limitation, due to its restrictions on collecting historical data. While we used two 1-week collection periods, the date ranges for collected data varied between athletes. The variation in historical retrieval can be attributed to several factors including how active an account is on Twitter. For example, an athlete considered highly active may have a historical retrieval limited to 2 months. However, an athlete with limited activity may have historical tweets scraped from within the previous year. This limitation does not allow for control of significant external events that could affect attention received on Twitter or other popular media outlets. Ideally, historical data collected would cover the same period for all athletes to offset any inconsistencies and allow for greater control of outside influences. That said, Twitter API limitations are acknowledged in this area of research, but it still provides a preliminary starting point to understanding fan response to sponsored messages (Blaszka et al., 2012).

Another limitation is that some of the data collected (specifically, the number of retweets and number of followers) is inherently nonnormal. As previously mentioned, it was our intention to include each athlete's number of followers as a covariate, but the nature of the nonnormal variable led to a gross homogeneity-of-regression violation (thereby dramatically increasing Type II error), thus forcing the removal of the covariate. Essentially, there were 16 tight clusters of values centered on the mean followers for each athlete. Put differently, the change of followers within athletes was very small, but the change between athletes was very large. It is worth noting, however, that significant differences in gender (where the follower discrepancy would have had the greatest effect) were also found in the model with followers included as a covariate, despite the fact that Type II error was likely increased in that test. Thus, it appears that there were still significant differences on retweets between male and female athletes, regardless of the disparity in followers; however, future research is necessary to verify this finding.

Future research should continue to examine other aspects of information diffusion. While outside of the scope of this study, it would be important to determine if certain message characteristics can drive information diffusion across multiple nodes or "hops" of a network (Yang & Counts, 2010). In addition, sport social-media researchers should consider the relationship between large events and the timing of social-media posts, in regard to information diffusion. These findings could determine optimal windows for posting content on social media leading up to events where message exposure and a potential for information diffusion are maximized.

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