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Networked Fandom: Applying Systems Theory to Sport Twitter Analysis

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The purpose of this study was to employ systems theory to analyze the social network of a Big Ten football team's Twitter community. An identifiable network was found among the observed actors ($N = 139$), with fan accounts composing the largest percentage of the network. The number of observed reciprocal interactions was low, only 11.8% of the interactions and only 21.5% of the nodes. Traditional-media accounts frequently interacted with other media accounts, while fans interacted primarily with other fans. Overall, nontraditional-media accounts' users were most focused on interactivity. Team-related accounts were almost nonexistent in the interactive network. A systems-theory-based network was found in terms of input, transformation, and output components. The feedback loop was the weak link in the network, indicating a possible lack of importance of direct feedback in Twitter social networks.

Keywords: social media, connectivity, users, social networking

As dynamic as they are ever-changing, social-media platforms have had a pronounced effect on user interaction (Phua, 2010; Wallace, Wilson, & Miloch, 2011). These effects have been felt in various industries including sport (Pegoraro, 2010). One social-media platform that has begun to reshape the sport landscape is Twitter. With nearly 200 million users worldwide (Shiels, 2011), Twitter has rapidly become part of the sport firmament since it was first introduced in 2006 (Clavio & Kian, 2010; Tsukayama, 2011; Wertheim, 2011). Although Twitter use among sport entities (i.e., teams, athletes, and leagues) has increased dramatically in recent years (Fisher, 2009), there are various usage trends and components of the medium that have yet to be explored in their entirety.

Previous sport-specific research has investigated how Twitter can serve as a vehicle for interactivity, information sharing, and promotion among its users (Hambrick, 2012; Hambrick, Simmons, Greenhalgh, & Greenwell, 2010; Kassing

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& Sanderson, 2010; Pegoraro, 2010). While this line of research has also begun to demonstrate how fans (Clavio & Kian, 2010), athletes (Hambrick et al., 2010; Pegoraro, 2010), and organizations (Sanderson, 2011) use Twitter, little attention has been paid to specific characteristics of users' Twitter feeds (Clavio & Kian, 2010). More important, it appears that only one study to date (Hambrick, 2012) has examined social-network formation on Twitter. That is troublesome, given that social media are intended to promote "conversation, collaboration, and community" (Marez, 2009, p. 682). Furthermore, if in fact social media are meant to "facilitate human connections" (Sanderson, 2011, p. 494), then a greater understanding is needed regarding the formation of social networks within Twitter's often-decentralized world. The value of understanding how people interrelate and act in a social network is incredibly high, as postmortem examinations of failed social networks have revealed the overwhelming importance of the community of users to social-media success (Madrigal, 2012).

Therefore, the purpose of this study was to employ the conceptual framework of systems theory to examine user characteristics of a sport-specific social network on Twitter. Specifically, this study examines the social network of a Big Ten football team's Twitter community. This is accomplished through social-network analysis, which is a common methodological approach to examining social relationships (Lusher, Robins, & Kremer, 2010). This study is an early attempt to apply systems theory to a sport and social-media context. In addition, the systems-theory approach has yet to be used in conjunction with social-network analysis on Twitter.

Social-Network Analysis

Networks, as defined by Crossley (2010), are "what link the millions of 'actors' in a complex structure, constituting them as a system" (p. 342). According to Quatman and Chelladurai (2008b), a network is representative of the relationships between individuals in a system. To examine networks and their relationships, Moreno and Jennings in 1933 conceptualized the process of "sociometry" (Quatman & Chelladurai, 2008b, p. 340). Sociometry, the predecessor to network theory (Granovetter, 1973), or social-network theory, was a methodology used to create the structure of groups, in which individuals or units were represented as points on a graph with relationships illustrated by lines connecting units (Quatman & Chelladurai, 2008b). This process was refined over the decades to what is now known as social-network analysis, a methodological approach that has been tied to the phrase *social network theory,* which falls under the larger network perspective (Quatman & Chelladurai, 2008a).

The conceptual viewpoints behind social-network analysis are based on social-network theory, sometimes referred to as network theory, which is centered on the premise that the world contains various groups who form systems of relationships (Emirbayer, 1997). According to social-network theory, the behaviors of individuals are a byproduct of the construction of the system itself, as opposed to the normative behaviors of individuals affecting social constraints, which govern the system. Although sociometry provided a methodology for illustrating the structure of groups, scholars began to further explore the relationship components between individuals in a network, such as characterizing the strength of relationships as strong or weak (Granovetter, 1973). This assisted in conceptualizing the structural components of sociometry in a more theoretical perspective by relating interpersonal relationships with "macro phenomena as diffusion, social mobility, political organization, and social cohesion in general" (Granovetter, 1973, p. 1361). Due to the increased focus on the relationships in a network, in the network perspective a social network is defined as "a set of nodes (e.g., persons, organizations) linked by a set of social relationships (e.g., friendship, transfer of funds, overlapping membership) of a specified type" (Laumann, Galaskiewicz, & Marsden, 1978, p. 458). This conceptualization of the study of social networks allowed academics to examine individuals and the systems in which they exist. The conceptualization was aided by the methodological approach of social-network analysis.

Using Emirbayer's (1997) idea of relational thinking, social-network analysis was employed as a methodological approach (Quatman & Chelladurai, 2008a) that operationally defined the theoretical concepts of nodes and social relationships in a social network to study social structure (Wasserman & Faust, 1994). Using this methodological approach, academics look at the relationships between individuals, rather than having to focus on the individuals as separate entities, through the graphic depiction of nodes and social relationships in a sociogram (Wasserman & Faust, 1994). This does not mean that individual features are not accounted for in social-network analysis, as they can be examined, as well, to see how individual attributes affect the relationships in the system. According to Wasserman and Faust, the system is defined as collective groups of individuals or the entire network. In an online environment, social-network analysis has been employed to examine the network structure of an online community for smoking termination (Cobb, Graham, & Abrams, 2010), the construction of online extremist political networks in Italy and Germany (Caiani & Wagemann, 2009), online and social-media roles in social-image construction (Gilpin, 2010), and the construction of an online knowledge-building community (Myllari, Ahlberg, & Dillion, 2010).

In sport literature, social-network analysis has been used to investigate team dynamics in sports such as baseball (Lusher et al., 2010) and basketball (Warner, Bowers, & Dixon, 2012), network formation around a community basketball program (MacLean, Cousens, & Barnes, 2011), knowledge and information spread in the field of sport management (Quatman & Chelladurai, 2008a), and ontological, epistemological, and methodological contributions to the field of sport management (Quatman & Chelladurai, 2008b). An examination of the existent sport communication literature yields only one study to date that employed social-network analysis to examine social-media use in a sport context. Hambrick (2012), through social-network analysis, examined how two bicycle-race organizers used Twitter to promote their events.

Based on the definitions of a network by Crossley (2010) and Quatman and Chelladurai (2008a), to determine if a network exists, relationships between actors would need to be identified. Previous studies examining online social networks have identified the presence of relationships through analysis that examined whether individuals exchanged messages in an online environment (Cobb et al., 2010; Myllari et al., 2010), the use of specific terms by an organization on different online platforms (Gilpin, 2010), providing links on a Web site to other Web sites that contained similar content (Caiani & Wagemann, 2009), and, specific to Twitter, the process of posting tweets and the subsequent following of a Twitter feed based on tweet content (Hambrick, 2012). For the purpose of this study, the presence of relationships was defined using the designations by Cobb et al. (2010), Myllari et al. (2010), and Gilpin (2010). The presence of a relationship between actors, which constituted a network, was defined as the use of specific terms, a hashtag or the word *football,* and interactivity between actors who used those specific terms. However, as the sport-related social-network literature is varied, and network structure cannot be predicted, the following research question was developed to guide the study:

> **RQ1**: Is there an identifiable network (or networks) in the observable subset of Twitter users for a Big Ten football team?

One element of social-network analysis is the various actors in a network. As part of a social-network analysis, a visual representation of a network of individuals is produced, which is referred to as a sociogram (de Nooy, Mrvar, & Batagelj, 2005). Individuals, or actors, in the network are represented as nodes in the sociogram, and the various relationships, or ties, between actors are illustrated as lines (Quatman & Chelladurai, 2008b; Lusher et al., 2010). Not only does social-network analysis allow for examination of the relationships between actors in a network, it also allows for the potential to differentiate between different classes of actors in a network (i.e., attributes of individuals). For example, in their study on an online community for smoking termination, Cobb et al. (2010) identified actor classes including smokers and nonsmokers and male and female members. Caiani and Wagemann (2009), in their study on online networks on the Italian and German far right of the political spectrum, identified different actor classes based on political party affiliation. Employing social-network analysis in an online environment may allow for further actor classification, as the features of the Internet, and the various media platforms it supports, allow for information sharing throughout a large geographical area (Burgelman, 2000). This could increase the potential size and construction of the network.

Previous research studies investigating Twitter use in the sports industry have found athletes and fans to be two classes of individuals communicating on Twitter (Clavio & Kian, 2010; Hambrick et al., 2010; Kassing & Sanderson, 2010; Pegoraro, 2010). Local and national sporting events (Hambrick, 2012; Schoenstedt & Reau, 2010), college athletic departments (Sanderson, 2011), and traditional-news-media members (Schultz & Sheffer, 2010; Sheffer & Schultz, 2010) are additional classes of individuals using Twitter. While those studies contributed to the body of literature investigating social-media use in sports by identifying how the mentioned classes are using the medium, little investigation has focused on the formation of social networks around sports (Hambrick, 2012). As such, the following two research questions were developed:

> **RQ2**: How do previously identified actor classes interact with one another within the observed Twitter network subset?

> **RQ3**: Are there observable differences in the way actor classes interact within this social network?

There are many key concepts that are central to the conversation in social-network analysis, including the concept of actors operating within a system (Wasserman & Faust, 1994).

As social-network theory, on which social-network analysis is based, posits that the behaviors of individuals are a byproduct of the system in which they operate (Emirbayer, 1997), a conceptual framework that incorporates the structure of the system may further the understanding of interaction within the system.

Conceptual Framework

Ludwig von Bertalanffy first conceptualized systems theory in 1968 as part of general systems theory. General systems theory was conceived as a mathematical model through which principles of a system, such as wholeness, differentiation, centralization, and equifinality, could be measured (von Bertalanffy, 1972). A system, as defined by von Bertalanffy (1968), is "a set of elements standing in interrelation among themselves and with environment" (p. 252). Almaney (1974) further defined a system as "any set of interrelated elements that form a unified or complex whole" (p. 35). A primary consideration in the development of general systems theory was the concept of an "open system" (von Bertalanffy, 1972), a system that interacted with its environment. Although von Bertalanffy (1972) first employed general systems theory to aid study in the field of biology, systems theory has been applied to the study of systems in multiple disciplines including the field of physics (e.g., Fenn & Fayer, 2011) and the social sciences such as business management (e.g., Guenzi, De Luca, & Troilo, 2011; Roche & Teague, 2012).

When one examines systems from a communication viewpoint, cybernetics can also become an area of focus. Cybernetics, a branch of systems theory that includes feedback loops (Littlejohn & Foss, 2010), examines processes in a circular fashion and was defined by Wiener (1948) as the study of control and communication in both mechanical and living systems. Thus, cybernetics has been used to examine systems in the areas of engineering (e.g., Bejan, 2011), computer sciences (Xian, Huang, & Cobb, 2011), and communication (e.g., Engesser & Franzetti, 2011). In cybernetics, according to Kefalas (2011), a system is composed of objects, attributes, internal relationships, and an environment, where the objects are the components in a system and the attributes are the qualities of the objects. However, Kefalas (2011) states that functionally, the objects in a system can be the tasks performed by the system parts, which include the inputs, throughput (process), outputs, and feedback loop. The input induces activity in the system, and the throughput or process converts the input into results. The output is the outcome of the process, while the feedback loop can help maintain balance in the system by connecting inputs to outputs. Finally, the environment is the setting of a system.

Based on the use of cybernetics to examine communication, and its employment in the area of computer sciences, the model by Littlejohn and Foss (2010) was used as the proposed system for this study, as it examines communication on an Internet-based medium (i.e., Twitter). The elements of the model were operationally defined in this study to examine the proposed system in a Big Ten football team's Twitter community. Therefore, an input was operationally defined as a message originator in the Big Ten football team's Twitter community. The throughput was defined as the social-media platform Twitter. The output was defined as the message receiver in the Big Ten football team's Twitter community. The feedback loop was defined as a response from the message receiver back to the message originator, and the environment was defined as the collective Big Ten team's Twitter community. The use of this model enabled us to examine the behaviors of individuals as a byproduct of the system (Emirbayer, 1997) and resulted in the development of the following research question:

> **RQ4**: Does the proposed system appear to exist, in accordance with the tenets of systems theory?

Methodology

The methodology used in this study is a social-network analysis. This methodology was selected as it has been previously used in research to examine social relationships (e.g., Lusher et al., 2010) and online communities (e.g., Caiani & Wagemann, 2009; Cobb et al., 2010). To create the social network of the Big Ten football team's Twitter community, the methodology of the study was conducted in two parts. Part 1 involved creating the boundary for the social network by identifying users of the Big Ten football team's official hashtag during a defined period of 1 week during the opening portion of the 2011 season. Part 2 involved examining the relationships between the actors identified in Part 1, by capturing and analyzing their interactive tweets during a regular-season football game. The online collection software DiscoverText (http://discovertext.com), text-analytic software that facilitates the import of data from various sources and formats such as Twitter, was used to collect tweets and create a static data set for analysis. The team in question was chosen due to its athletic department's active social-media efforts, the consistent use of the Twitter hashtag by fans, and the overall popularity of Big Ten football.

Part 1 of the methodology involved creating a boundary for the Big Ten football team's Twitter community. To create the boundary, all tweets mentioning the school name and *football* or using the designated football hashtag from the school were collected during a 1-week time period from August 30 through September 6, 2011, which included the first game of the 2011 season. This created a purposive, consecutive-day sample that identified the specific individuals related to the purpose of the study (Riffe, Lacy, & Fico, 2008). The sampling strategy resulted in the identification of 780 individuals who used the search term or hashtag in 1,349 tweets. The 780 individuals were operationally defined as the potential population of actors in the network and were both message originators and message receivers, consistent with the proposed system used as the conceptual framework.

Part 2 of the methodology involved examining the relationships between the actors in the network. To examine the relationships of actors during a regular-season, Big Ten football game, all actors identified in the population were followed in a separate Twitter feed constructed by the researchers. When importing data for analysis into DiscoverText, the user has the option to import based on keywords used in tweets or to import a singular, specific Twitter feed's follower list. By creating a separate Twitter feed to follow all actors in the population, DiscoverText could capture tweets produced by the actors during a specific time frame. All tweets produced by the 780 actors were captured on October 11, 2011, during a Big Ten football game. This game was chosen due to its placement in the middle of the regular season and because it represented a typical Big Ten football game, as the two squads involved are not considered traditional rivals. This created a purposive sample of tweets collected every hour from 2 hours before the game through 2 hours after the game. The total number of tweets gathered during this 1-day time frame was 2,219. Employing the conceptual framework for the proposed system, we analyzed the 2,219 tweets produced by the actors in the population for interactivity. Only actors who tweeted to other actors in the network or were the recipients of tweets from other actors were retained. Thus, tweets between actors were operationally defined as ties within the network. In regard to "retweets," only traditional-style retweets were included in the analysis, due to their structure. A traditional retweet is structured as a normal Twitter reply would be, with the actor placing an "RT" in front of the recipient's name. This is counted as an interaction within the Twitter network. The newer-style retweets, which require only a button push and do not necessitate any interactivity on the part of the retweeter, were not considered as part of this analysis; we instead opted to focus on the stricter, more active definition of *interactive*. In addition, consistent with the operational definition of the proposed system, which defined the throughput as Twitter and included a feedback loop defined as a response, ties in the network were binary. As indicated by Lusher et al. (2010), ties between two actors, for example actors a and b, could be present or not. This is operationally defined as $x_{ab} = 1$ for present ties and $x_{ab} = 0$ for nonpresent ties.

In addition to identifying the interactive actors from the population, an observational analysis of the 2,219 tweets was employed to identify the various potential actor classes. The observational analysis produced five actor classes: team-related users (i.e., athletes, coaches, sport information directors), traditional-media users (i.e., reporters, network analysis personnel), nontraditional-media users (i.e., bloggers, podcasts, independent media Web sites), fans, and ancillary users (i.e., fake Twitter accounts). To assign actors to their respective actor classes, we examined the biographical information they provided on their Twitter feeds. Actor Twitter names, which were collected as a variable, were assigned a number and entered along with their respective actor classes into a sociomatrix.

According to Lusher et al. (2010), a sociomatrix is a table consisting of n rows by n columns, where n is the total number of actors in the proposed network. Values entered into the rows and columns in the table were the binary values (i.e., 0 or 1) based on present or nonpresent ties, or relationships, between the actors. Once the data were placed in the sociomatrix, a sociogram of the network was produced using the social-network analysis programs UCINET and NetDraw.

Results

The first step in evaluating the potential application of systems theory to this proposed social network was to ascertain whether there was an identifiable network in the observable subset of Twitter users for the chosen team, as detailed in RQ1. After analyzing observed nodes, we determined that an identifiable network did indeed exist. This was based on the presence of relationships that were identified through consistent interactivity between the observed nodes, as well as the clustering of interactions around certain types of nodes, forming subnetworks in the observed network. An examination of actors engaging in interactivity, per the proposed systems, yielded an identifiable network with a node total of 139 (N = 139). This represented 17.8% of the total potential actors in the network. Each of these actors engaged at least once in interactive activity via Twitter with another preidentified potential actor during the prescribed time period of data collection. Of this total, 30 actors engaged in reciprocal interactive activity (21.5%), while the remainder engaged in one-way interactive activity.

In addition, the five previously identified actor classes were each assigned a color and placed in the sociomatrix to aid in examination of RQ1, RQ2, and RQ3 and to assist in visualization of the network. The actor-class colors were defined as follows: athletic department and team-related users (red); traditional-media (i.e., newspapers, television) users (blue); nontraditional-media (i.e., blogs, message-board Web sites) users (black); fans (yellow), and ancillary users (i.e., fake accounts; green). The visual results of the sociomatrix are represented in Figure 1.

In evaluating the nodes of the observed network, all nodes fit easily within one of the five predetermined classes. The largest single class of actors in the network was fans, who composed 84 of the 139 observed nodes (60.4%), while the actor class with the lowest observed number was team-related accounts (n = 5, 3.6%).

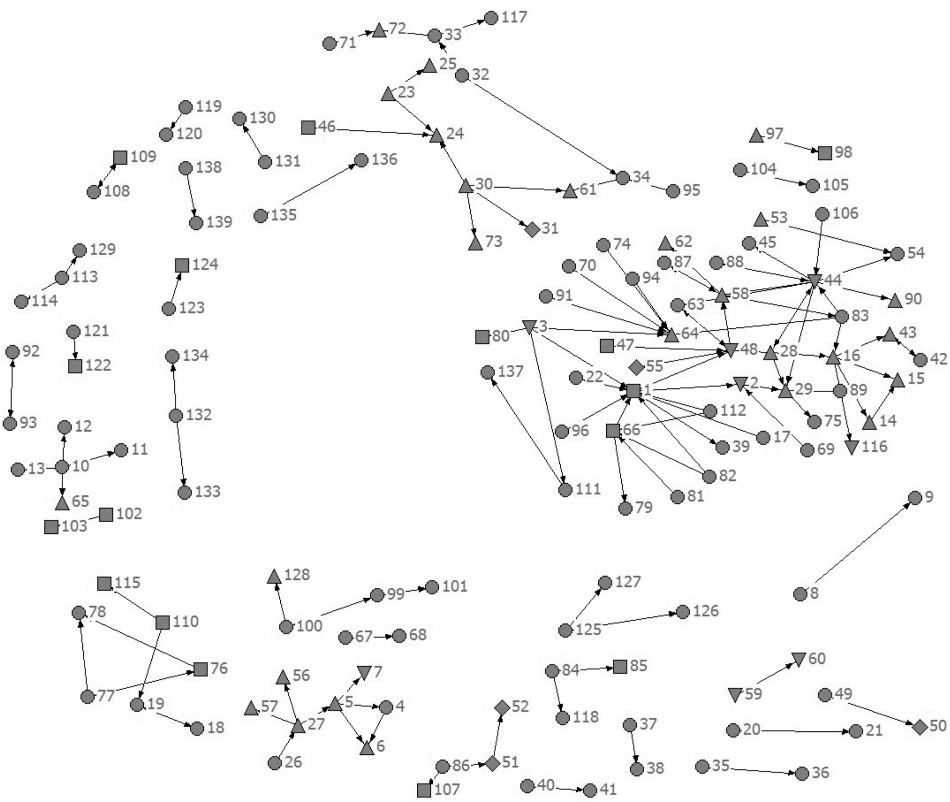

Figure 1 — Result of social-network analysis with nodes separated by class type and lines indicating message direction and interactivity. *Note*. Fans = circle; traditional media = up triangle; nontraditional media = down triangle; ancillary/fake accounts = square; team-related = diamond.

RQ2 asked how actor classes interacted in the observed network. Analysis of the network indicated that the primary type of interaction was one-way in nature. In total, there were 127 interactions observed, with 15 of those interactions being reciprocal (11.8%). The network contained one primary area of group interaction, in which the largest amount of interactions was present. There were, additionally, two smaller areas of group interaction. The rest of the interactions were generally peer-to-peer only, with some interactions involving three individual nodes.

RQ3 asked whether there were observable differences in the way actor classes interact in the network. There did appear to be detectable differences, particularly in relation to reciprocal interactivity. Of the 30 actors engaged in observed reciprocal interactions, 17 involved fan nodes, 6 involved traditional-media nodes, 3 involved nontraditional-media nodes, 3 involved ancillary nodes, and 1 involved an official team node. Only one reciprocal interaction did not involve a fan node, instead involving an interaction between a traditional-media node and a nontraditional-media node. As a percentage of node type, 20.2% of fan nodes engaged in reciprocal interactions, compared with 23.1% of traditional-media nodes, 33.3% of nontraditional-media nodes, 20% of ancillary nodes, and 20% of team-related account nodes.

An examination of total interaction (both one-way and reciprocal) revealed that fan nodes initiated the most interactions, both as a total number (71) and as a percentage of total nodes (84.5%). A plurality of fan-originated interactions were aimed at other fans (34, 47.9%). Table 1 illustrates the spread of interactions, based on senders (origin) of Tweets and receivers (destination). Table 2 highlights the total number of observed interactions as a percentage of total node type. In this table, a rate of 100% would indicate that the number of originated interactions was the same as the number of nodes of that type in the network. Two node types, nontraditional media and traditional media, had more interactions than observed members of the network, indicating that these node types originated more than one interaction per network member for that class.

Discussion

In evaluating the results generated by this study, we see several interesting items emerge. RQ1 posed the question of whether there was a network in the subset of Twitter users for a Big Ten football team, and the result was affirmative. Based on the interactivity of the nodes examined, a network was found in the Twitter users examined, and the users in that network engaged in both one-way and two-way interactive behavior.

RQ2 dealt with the issues of how actor classes were interacting with one another inside the network, while RQ3 asked whether there were observable differences in how they interacted.

Interactivity analysis illustrated that the most active group of participants were media members, both traditional and nontraditional. Both of these groups created interactive tweets that exceeded their numerical position in the network, indicating that these media outlets were possibly acting as agenda setters or opinion leaders. As stated by Hambrick (2012), actors with numerous relationships can act as hubs of information, increasing the life span of the message. In this instance, the traditional- and nontraditional-media members could potentially occupy the role of

Table 1 Social Network Interaction Analysis

	Interaction Receiver					
Interaction sender	**Ancillary**	**Fan**	**Nontraditional media**	**Official**	**Traditional media**	**Total**
Ancillary	3 (25%)	6 (50%)	2 (16.7%)	0	1 (8.3%)	12
Fan	13 (18.3%)	34 (47.9%)	5 (7%)	2 (2.8%)	17 (23.9%)	71
Nontraditional media	2 (13.3%)	5 (33.3%)	1 (6.7%)	1 (6.7%)	6 (40%)	15
Team-related	0	1 (50%)	0	1 (50%)	0	2
Traditional media	1 (3.7%)	7 (25.9%)	4 (14.8%)	1 (3.7%)	14 (51.9%)	27

Note. Percentages refer to row totals.

Table 2 Node Types and Percentage of Total Interactions by Node

Node type	Node count	Interaction as % of total nodes
Ancillary	15	80%
Fan	84	84.5%
Nontraditional media	9	166.7%
Team-related	5	40%
Traditional media	26	103.8%

agenda setters or opinion leaders due to their role in the network as an information hub. Traditional-media accounts in particular garnered a great deal of attention from other accounts, as just under 25% of interactive tweets from fans were directed toward traditional media. Traditional-media accounts also tended to interact greatly with each other, as over half of the interactive tweets that originated from these accounts were directed at other traditional-media accounts. Nontraditional-media accounts, which represented blogs, message boards, and other Internet-only sports media, appeared to possess the users most focused on interactivity, as several members of this class had multiple interactions.

In both media cases, the high percentage of interactivity, both inbound and outbound, creates interesting future study opportunities. Empirical observation of the accounts and tweets sent by these media-class members demonstrated that they held running conversations with each other throughout the game and appeared to communicate more easily and comfortably than similar interactions observed between fans and either media type. Indeed, all three of the noted areas of interaction within the network appeared to center on interactions between traditional-media accounts or between traditional- and nontraditional-media accounts. The core users of the primary interaction, for instance, appear to be traditional-media nodes 64, 58, 28, 16, and 29; nontraditional-media nodes 3, 48, 2, and 44; and ancillary nodes 1 and 66. The two ancillary nodes were both "fake" accounts of members of the coaching staff, and one of these accounts actually maintained a regular media appearance on a team-focused blog during this season.

These areas of interaction within the network represented cohesive subgroups. In a cohesive subgroup, members of the network are likely to communicate frequently (Quatman & Chelladurai, 2008b). The inclination of actors to form cohesive subgroups in a network is related to the concept of homophily, in which people tend to form relationships with others who share similar characteristics (Lusher et al., 2010). Homophily in the network could result in increased transitivity, which is defined as the tendency of individuals to form triadic relationships with others, as social relations are rarely random (Crossley, 2010). As a result, these cohesive subgroups can also represent "small worlds" (Crossley, 2010, p. 358) within the network. As the behaviors of actors in the network are a byproduct of the network itself (Emirbayer, 1997), the formation of the cohesive subgroups in the network would facilitate the continued communication between members of the subgroup. The presence of cohesive subgroups in this study is consistent with previous literature, as cohesive subgroups are found to be present in other networks, as well (Caiani & Wagemann, 2009; Cobb et al., 2010; Quatman & Chelladurai, 2008a). Further investigation into the patterns of use among sport media in identified social networks may yield further insights into how the media affect the overall focus of the conversation, or if the information provided by media remains internal to the cohesive subgroup.

The fan accounts occupied the median interaction position, and some fans were certainly more interactive than others were. Certain fans appeared most interested in participating in the metaconversation occurring with traditional and nontraditional media, and in a few cases, these conversations turned reciprocal. However, most of the interaction with fans came from other fans, and many of these conversations were quite isolated from any collective interactions being held. This is a curious finding, as previous sport-related Twitter research has identified interactivity as a gratification for fans (Clavio & Kian, 2010; Hambrick et al., 2010; Pegoraro, 2010), and this could indicate that the number of sports fans using Twitter for interactive purposes is lower than has been surmised.

Ancillary accounts, as mentioned earlier, consisted primarily of fake accounts relating to coaching staff, players, and other personnel related to the team. Aside from two accounts, these ancillary nodes did not appear to drive much interactivity. Finally, team-related accounts were nearly nonexistent from the network analysis, and only one account engaged in interactivity with an account that was not also a team-related node. This represents a considerable void for this particular team's athletic department, as the lack of participation by their accounts in the social network surrounding the team allows media accounts and fans to dictate the content of the interaction taking place in the network. The team-related accounts were not absent from Twitter during the game, as they were regularly tweeting updates and statistics throughout; however, they engaged in practically no interaction.

One possible explanation for this finding relates to the policies and views of Division I athletic departments in regard to social-media use. According to Sanderson (2011), Division I athletic departments promote Twitter policies that are content-restrictive in nature, as they view participation in social media as an inherently risky endeavor. This is an area that warrants further examination, both in future social-network analysis and in surveys and interviews with college athletic departments, to fully determine their attitudes toward social-media engagement with fans and media.

RQ4 asked if the proposed network appears to exist in accordance with the tenets of systems theory, as highlighted in the literature review. Based on observations of the network and the node activity, a systems-theory-based network does exist, with some caveats. There is obvious evidence of input, as found in the interactive tweet originators, and there is evidence of an output process, as found in the interactive tweet receivers. The transformation element of this system is the medium of Twitter itself. The presence of the input, transformation, and output components of the system in this network aided in the communication process, particularly the transformation element, as Twitter can provide a platform to share information and provide commentary (Kassing & Sanderson, 2010).

The weak link in this system appears to be the feedback loop. Although some reciprocal interactions were found, the number was relatively low, only 11.8% of the interactions and only 21.5% of the actors. One possible explanation for this finding is that the network was more decentralized in nature, and, as such, no single actor was in a central position in the network (Quatman & Chelladurai, 2008b). The decentralization of the network could in turn indicate that there was no need for immediate feedback by actors, which is indicative of a more centralized network (Myllari et al., 2010). As stated by von Bertalanffy (1972), objects in a system are defined through their interaction with the components of the system. The characteristic of each component in the system does not make it unique, as Almaney (1974) indicated that the system "is dependent on the manner in which the components are structured and that patterns of interaction and interdependence existing among them" (p. 35).

The results of this study indicate that patterns of interaction occurred between the input, transformation, and output components of the system. Although this study used a system model based on the cybernetics tradition (Littlejohn & Foss, 2010) that included an open-loop feedback that exits from the output into the environment and back to an input (Almaney, 1974), the pattern of interaction in the system did not support the use of the feedback loop. As a result, components of the system defined as outputs (i.e., interactive tweet receivers) did not reintroduce themselves into the system as feedback inputs (Kefalas, 2011). It is possible that feedback was being generated through noninteractive means, such as retweets by interactivity targets or incorporation of sender messages into future receiver tweets without direct reciprocity. We should also consider the time for which this system was observed, only 8 hours. It is also possible that feedback may not be an important feature to those who operate within a Twitter social network. Further study is needed in this area, preferably with a broader set of actors and a wider time period, to see whether persistent actors or time affect this variable of the system model.

It is also curious that the number of observed interactive actors in the network was so small (17.9%) compared with the starting sample. It is important to note that this initial account was derived from a combination of hashtag use and mentions of the word *football* and the school name, rather than from any observed interactions external to the observed time frame. This methodology may need refining in the future to ensure the best possible acquisition of network actors. There may also be technological concerns regarding replies, where individuals may be able to read tweets but might not be aware of how to respond. Future studies should focus not just on interaction but also on the quantity of noninteractive posts that various nodes produce, to capture a broader perspective on the larger community of team-focused users. However, as stated earlier, the focus of this study was on the observed interactive nodes during the prescribed time period.

There are several practical implications in the findings in this study. The existence of an identifiable network, and connected subnetworks, points to a goal-directed use of Twitter and social media by both audience members and media members. As a result, the image of the sport organization that the network focuses on is being affected by the activities of the network. It is important for sport organizations to understand the various aspects of these networks, for a variety of reasons. In terms of understanding users, sport organizations need to know who is actively talking about the team and its stakeholders and what the nature of these users is. Are these alumni, boosters, nonalumni fans, rival-team fans, bloggers, traditional media, or some other type of individual? In some cases, these users may represent key target markets, either for conventional ticket purchases or for larger scale giving.

In other cases, they may represent opinion leaders, particularly in the case of users who act as hubs of subnetworks within the larger network. In all cases, learning what the active audience in a sport organization's network consists of can assist those organizations in efforts relating to marketing, public relations, and sales. By knowing who the users are, the team can engage these users directly, based on the content of their messages and the manner in which they communicate.

Another practical implication is the potential for sport organizations that are not interacting with their constituents on social networks to lose control of the narrative, so to speak. Drawing on the theoretical principles of agenda-setting theory (e.g., McCombs & Shaw, 1972), which states that the media do not tell us what to think but are effective at telling us what to think about, the implications of a noninteractive sport organization in an interactive sphere such as a social-media network could be considerable. By allowing other, nonaffiliated accounts to be primary purveyors of interactive opinion in the social-media network of fans and stakeholders, sport organizations run the risk of those individuals being seen as the primary source for such opinions. The existence of sport social-media networks means that sport organizations need to be cognizant of the ideas and opinions being shared in these networks and should consider engaging in interaction with the networks' users or be seen as simply providers of information, rather than as interactive members of the online community.

Conclusions

The purpose of this study was to extend sport social-media literature by examining the potential application of systems theory to a network of fans using Twitter as their medium of interaction. This study builds on the prior work of Hambrick (2012), Kassing and Sanderson (2010), Schoenstedt and Reau (2010), and other scholars who have looked at social networks and sport fan activity in the realm of social media. The findings of this study demonstrate the existence of a measurable social network that fits within the tenets of systems theory and lay the groundwork for subsequent study of this important phenomenon.

This study did have some limitations. As it only focused on a single potential social network centered on a singular event, the breadth of the social network was, not surprisingly, low. Further research should expand both the number of potential actors and the time period studied. In addition, while social-network analysis of this type is useful for illustrating interactivity-focused Twitter use, it does not capture observational or informational Twitter use, which composes a considerable percentage of Twitter use overall. It is possible that Twitter users consider themselves part of this larger social community but would not show up in this type of analysis without expressing themselves interactively. Finally, this analysis was restricted to actors who had been observed and identified beforehand, thereby creating the possibility of actors missing from the analysis who are actually a part of the network. A broader and more long-term collection process should be used in the future to derive the potential membership of the network and ensure that any users left out of the analysis are kept to a bare minimum.

Future studies should focus on other sport Twitter structures, both those that concentrate on large-scale events such as the Olympics and those that focus on more day-to-day interactions between fans, media, and teams, such as those found in a Major League Baseball season. The inclusion of informational or observational Tweets in the network analysis is also a promising avenue for research, as the combination of these with interactive analysis could present a more multidimensional approach to examining the nature of the network and the flow of information and opinion. Furthermore, additional studies of this type should focus on the agenda-setting power of traditional media-controlled accounts within the confines of a sport social network, to see if these media entities are attempting to maintain control of the agenda through social means. In addition, this method can and should be extended to other sport social media such as Facebook, Pinterest, and Instagram, to see if systems theory can shed further light on the manner in which these networks of fans and stakeholders coalesce.

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