Social networks have been influential in society since humans began social interactions. Social networks provide people with resources including trust, information, and influence (Coleman, 1990; Demsetz, 1991), referred to as social capital (Yang, Keller, & Zhang, 2017). Individuals have a restricted capacity to gain knowledge, therefore collaborating with others is essential to gather knowledge (Borgman & Furner, 2002; Lin, 2001). A person's position in a social network can define the limitations and options available (Borgatti, Everett, & Johnson, 2013). The achievement of an individual may be related to the resources accessible to them through social connections (Lin, 2001).

Connections enable actors to achieve goals by giving them access to resources within the network (Yang et al., 2017). By leveraging social networks, academics can share the load of large-scale research projects and capitalize on the talents, skills, and expertise of others (McFadyen, Semandi, & Cannella, 2009). "A network of connections can provide help, support, opportunities, and even a sense of well-being that would not otherwise be possible" (Scott, 2017, p. 2). Connections provide social capital people can use to strengthen their potential for gain and opportunity (Scott, 2017). In academia, these relationships and social networks can be illustrated and examined through coauthor network analysis.

Social network analysis was chosen because "the network perspective makes it easier to build the connection between the individual behavior and the systemic changes or vice versa" (Yang et al., 2007, p. 14). In other words, coauthorship benefits individual authors while also affecting the larger system of agricultural communications researchers. Social networks have been analyzed in some form since the 1930s (Scott, 2017). However, it was not until the 1960s that formal and solid analysis methods were established. This type of data analysis is the culmination of work by anthropologists, sociologists, psychologists, and physicists. Researchers in each of these fields saw the value in quantifying group dynamics, interpersonal relationships, and their cumulative effect on the larger network (Scott, 2017).

Social network analyses can use attribute or relational data. Attribute data refers to the attitudes and opinions of the participants. The present study focuses on relational data, which describes connections (Yang et al., 2017). In this case, the structure of coauthorship represents these connections. Relational bibliometrics is a method of social network analysis that diagrams the structure of coauthorship and other bibliographic components from written publications including journal articles, proceedings, and books. Through relational bibliometrics, the progression of a discipline can be measured and the level of collaboration quantified (Benckendorff & Zehrer, 2013). These types of studies have helped other disciplines progress, grow, and share knowledge more efficiently.

Relational Bibliometric Studies in Other Disciplines

Relational bibliometric studies are commonplace in other disciplines, including public relations, business, natural sciences, psychology, and tourism and hospitality (De Solla Price & Beaver, 1966; Glanzel & Schubert, 2004; Koseoglu, Rahimi, Okumus, & Liu 2016; Li & Law, 2013). The typical goal of these studies is to examine and visualize collaboration among researchers. The first study of social networks in academia can be credited to Derek De Solla Price and Donald Beaver. They sought to describe the research groups in physics, specifically the ingroup. It was found the ingroup not only existed, but also dominated the research front (De Solla Price & Beaver, 1966).

Studies conducted in larger disciplines, like tourism and hospitality, analyze more than one journal and study larger sample sizes. These disciplines are seeking to conceptualize the network of researchers in their respective fields. When these types of studies are repeated at regular time intervals the evolution of the discipline and its contributors are revealed. These studies indicate that the more connections an author has, or the more collaborative he or she is, the higher number of publications an author will have (Servia-Rodrigues, Noulas, Mascolo, Fernandez-Bilas, & Diaz-Redonodo, 2015).

The *Journal of Applied Communications (JAC)* was chosen to examine the agricultural communications discipline. While agricultural communications researchers can publish elsewhere, *JAC* is the only journal solely dedicated to agricultural communications. Including other journals would expand the scope of the study but also obscure analysis of agricultural communications coauthorship by introducing non-agricultural communications scholars. While assessing the agricultural communications' connections with other disciplines has value, that was not the goal of this study. Using *JAC* as the publication parameter was deemed the best way to assess the social network of agricultural communications without including extraneous information.

The Agricultural Communications Discipline

Agricultural communications has grown significantly over the last 20 years. There are more than 40 programs nationwide (Miller, Large, Rucker, Shoulders, & Buck, 2015). *JAC* is touted as the premiere and primary journal in the discipline of agricultural communications (Rodriguez & Evans, 2016; Zumalt, 2007). The roots of *JAC* can be traced back to a newsletter called *ACE Quarterly,* which became *JAC* in 1990 (Journal of Applied Communications, n.d.). *JAC* is a peer-reviewed journal published quarterly by the Association for Communication Excellence in Agriculture, Natural Resources, and Life and Human Sciences (ACE). Its target audience is not solely academics, but anyone involved in agriculture, communications, and education (Telg, Tucker, & Dolbier, 2001).

By reviewing the research published in the agricultural communications, continued growth within the discipline is possible. Moreover, reviewing past research offers structure for future research (Miller et al., 2006). Agricultural communications researchers have examined *JAC* for various indicators of rigor and progression of the discipline (e.g., Baker & King, 2016; Miller, Stewart, & West, 2006; Naile, Robertson, & Cartmell II, 2010; Rodriguez & Evans, 2016). These studies examined theoretical rigor, research themes, scholarly progression, and research agendas of the discipline. Past studies have not addressed the structure of agricultural communications or author collaborations.

Previous studies found *JAC* was "meeting its purpose as a professional development resource for educational communicators" (Naile et al., 2010, p. 57). In a 2010 study, it was reported more than half of the articles in *JAC* from 1990 to 2006, were single-author publications (Naile et al., 2010). The structure of the agricultural communications discipline can be further understood by examining the coauthorship structure in *JAC*.

There are multiple opportunities to build connections between agricultural communications scholars. Agricultural communications researchers attend several annual meetings such as the ACE Conference, Agricultural Media Summit, National Association of Farm Broadcasters Conference, National Agricultural Communications Symposium (held at the Southern Association for Agricultural Scientists), and the American Association for Agricultural Education annual meeting. These meetings are tailored to specific aspects of agricultural communications work (i.e., research, teaching, professional, and service). Monthly professional development webinars are also offered by the Society of Agricultural Communications Scholars. There is even a Facebook group for agricultural communications faculty members.

All of these opportunities are meant to promote connections and diversification in the discipline of agricultural communications. However, there is no research assessing the connectedness and collaborations of academics in agricultural communications. This study sought to address that knowledge gap by assessing the social network of coauthorship in the *JAC*.

Components of a Social Network

Social network diagrams are made up of nodes and edges (Scott, 2017). Nodes are the individuals or actors who take part in the social network. Edges are the relations or ties between nodes. Social networks can be further analyzed by identifying and creating subgraphs or analyzing organically occurring cliques. A subgraph is identified by researchers and can be selected from any point in the network. The theoretical framework should act as a guide for selecting meaningful subgraphs. Subgraphs each have their own norms and outlook (Scott, 2017). In the context of this study, these norms and outlooks could be working styles, research interests, or even geographic location. Cliques are a distinct type of subgraph, usually more than three nodes, which are obvious when looking at the social network as a whole. Cliques are easily identified because the connections between nodes are denser (Scott, 2017). The strength of connections within cliques and social networks can vary.

Strong and Weak Ties

Ties within social networks can be categorized as weak or strong. There is much debate surrounding which is more preferable: strong ties with fewer people or weak ties with more people. The strength of a tie is quantified by the length of time it has been in existence and the amount of give-and-take between individuals (Rogers, 2003).

Strong and weak ties offer different advantages. Strong ties in a social network all but ensure a great amount of shared knowledge between those individuals. However, repeatedly returning to the same social network, or coauthors in this instance, could lead to stagnant ideas and knowledge. Strong ties often lead to higher levels of trust. This type of tie is more likely to result in critical evaluation of a peer's work (Levin & Cross, 2004). Networks with strong ties also share knowledge and information more effectively than networks with weak ties (Fritsch & Kauffeld-Monz, 2010).

Weak ties act as bridge links, connecting two otherwise unlinked groups. When weaker ties exist, new and different information can be passed between more social contacts. For example, in a study assessing job seeking information networks, it was found weak connections were of the most consequence when receiving information on job openings (Granovetter, 1973).

Homophily, the tendency for people who are alike to form connections, increases the likelihood of individuals working together (Yang et al., 2017). In the case of authorship, there are multiple avenues in which homophily could occur: working at the same institution, being alumni of the same programs, or having similar research foci. While demographics matter, they are not always the best predictor because position in the network matters. Coauthor analyses can show the way knowledge is built and disseminated within in a discipline (Yang et al., 2017). When examining social networks, heterogeneity of social networks, knowledge conversion, and innovativeness were positively related (Gronum, Verrynee, & Kastelle, 2012).

Social Capital Theory

The three basic types of capital in society are economic, cultural, and social. These can be exchanged for one another using "transformation labor" (Hauberer, 2011, p. 35). Social capital is capital gained through social relations. It can be used to ease the action of an individual (Yang et al., 2017). Social capital, like any resource, can be leveraged to benefit the holders (Kriesi, 2007). However, social capital is unique from other types of capital in a few ways. First, once social capital is leveraged, it inherently benefits all actors, making it a public good (Coleman, 1990). Second, it is shared and can never be the property of a single person (Burt, 1992). Third, gaining social capital is often a secondary outcome of other actions, such as coauthorship. One does not often intentionally engage in actions solely to build social capital (Hauberer, 2011).

While examining social networks and social capital can give insight about social links and disconnects between various people, institutions, or disciplines, it cannot directly assess the quality of work resulting from these connections (Scott, 2017; White, 2011). Quality of interactions cannot be assessed in the type of analysis in this project, but this study provided a necessary first step of describing the interactions occurring. This is essential in a knowledge-based discipline that values sharing knowledge with others.

Purpose & Objectives

The purpose of this study was to understand the network of coauthors in agricultural communications, specifically within *JAC*. "By examining the patterns of coauthorship, social network analyses can reveal the structures of knowledge formation and diffusion within one…discipline" (Yang et al., 2017, p. 47). The objectives of this study were the following:

1) Describe authorship, category (i.e., research article, commentary, book review), and number of *JAC* papers published from 2008 to 2017,
2) Describe the coauthor network characteristics of *JAC* papers, and
3) Describe the relationship between publication frequency and social network characteristics of authors.

Methods

Social network analysis "comprises a broad approach to sociological analysis and a set of methodological techniques that aim to describe and explore patterns apparent in the social relationships that individuals and groups form with each other" (Scott, 2017, p. 2). Social network analysis allows for the visualization of networks, as well as structural properties of networks (Scott, 2017). There are no defined rules for social network analysis; instead, researchers have to make informed choices when conducting and operationalizing analysis (Scott, 2017). Relational data, for instance, will result in quantitative data, but there is still an element of qualitative analysis needed for describing the network and its development (Scott, 2017). For example, within agricultural communications, the discipline is small enough to recognize sections in the social network that consist of individuals from the same institution. Further information can be sought online to determine where individuals received academic degrees, which was collected for the most-connected individuals.

Relational data, like those used in this study, can be inherently unwieldy due to the number of connections each individual can have. Therefore, boundaries have to be set by researchers (Scott, 2017). In this case, the target was coauthorship in agricultural communications. Archival data was used in the form of articles from *JAC* published between 2008 and 2017. Conference papers and posters were not included because those could have become journal articles, which could artificially inflate the weight of coauthor interactions. While this limits the scope of the articles included, it was deemed the best way to operationalize analysis. Furthermore, the 10-year timeframe was selected to create a parameter for the study to provide enough data to illustrate relationships over an extended period while remaining recent enough to be relevant to the current researchers in agricultural communications; 2017 was the most recent complete year of publication of *JAC* at the time of analysis.

Every article published in *JAC* in this timeframe was logged, including volume, issue, category (e.g., research, commentary, etc.), and author list. There were 189 articles published with 222 unique authors. Authors who published under different names during the 10-year period were considered one author. They are henceforth listed as the name most recently used in the timeframe. For objective 1, analysis included the number of articles by author, year, and type, as well as type by year and authors per publication. Frequency counts are reported, along with means for number of publications per author, number of publications as first author, and number of coauthored publications between coauthor pairs.

For creating the social network for objective 2, an undirected analysis was used because there is no inherent hierarchy between coauthors. Directed analysis indicates one person affects the other (e.g., a mentor affecting the viewpoint of a mentee), while undirected analysis does not indicate a direction of influence, just that the individuals are connected. Using directed analysis for this project was not feasible as available data does not quantify how or if authors influenced each other.

Each article was divided into an interaction between every coauthor, including the number of interactions between the authors (i.e., articles published together). For example, a two-author publication would have one unique interaction, and three-author publication would have three unique interactions, and so on. Single-author publications were excluded from the social network analysis because they did not contribute to the coauthor network. There were 503 unique coauthor interactions. Cytoscape, an open source network analysis program, was used to run the social network analysis and develop the visualization, which is described in the results section. Table 1 serves as a reference for interpreting network and node related data. The data reported to describe the entire network were: number of network components or nodes, network diameter, number of shortest paths, average shortest path, average number of neighboring nodes, network centralization, and network density. The data reported describing the social network attributes for nodes (i.e., authors) include degree, average shortest path length, betweenness centrality, clustering coefficient, and eccentricity. The data reported for edges (i.e., interactions between authors) includes number of interactions between a pair of authors and edge betweenness (i.e., number of shortest paths between other authors in the network that go through that specific edge). To aid in interpretation of the social network data, the academic history and lineage of the most connected authors were gathered from curriculum vitae, university websites, dissertations, and personal communication.

For objective 3, Pearson product-moment correlations were run between the number of publications an author has and the authors' social network characteristics. Statistical significance for the relationships was set as $p < .05$. For objective 3, correlations were described using Cohen's conventions. Pearson's r correlation was used, with a "weak" correlation defined as $.1 < r < .29$, a "moderate" correlation as $.3 < r < .49$ and a "strong" correlation as $r < .5$ (Cohen, 1977).

Table 1

Social Network Analysis Terms and Definitions Guide

Term	Definition	Operationalization
Node	The most basic element of the social network. A node represents the individual in the network.	An author in *JAC* from 2008 to 2017
Network diameter	The measurement of the longest of all shortest paths in the network	The number of links between the two authors furthest away from each other in the network
Average shortest path	Average number of people between a node and every other node in their network	Average number connections separating authors from each other in the network
Number of shortest paths	Total number of shortest paths in the network	The total number of paths to connect each author in the network to every other author in the network
Edge betweenness	Number of shortest paths that go through a specific pair	The number of shortest paths that use the connection between a pair of authors
Average number of neighboring nodes	The average for the whole network for how many nodes each node is connected to	The average number of coauthors for each author
Network centralization	Overall cohesion and integration of the network	The extent to which there is or is not a central hub of connection between authors in the network
Network density	Density of connections in network	The extent the network is populated by connections between authors versus isolated authors. If each author was directly connected to every other author, the network's density would be 1
Clustering Coefficient	Overall tendency for a node's neighboring nodes to be connected to each other	How much an author's coauthors publish with each other
Component	A cluster of connected nodes in the network who are not connected to other clusters of nodes in the network	If two authors only worked with each other and no one else, they would be a component
Degree	The number of other nodes a node is connected to	An author's total number of coauthors from 2008 to 2017
Connection	The link between two nodes	Two authors working together on a paper is a connection
Average shortest path length	The average distance between nodes in the network	Average number of connections between authors in the network

Term	Definition	Operationalization
Betweenness centrality	"Extent to which a node sits on the shortest paths between all other pairs of nodes" (Yang, Keller, & Zheng, 2017, p. 201).	The extent an author connects other authors who would otherwise be unconnected to each other (or would have to take a less direct route)
Eccentricity	The longest shortest path between the node and any other node in the network	The furthest any author is from the author in question

Results

Objective 1: Describe Authorship, Category (i.e., Research Article, Commentary, Book Review), and Number of *JAC* Papers Published from 2008 to 2017

Of the 189 articles, the majority were research articles (*n* = 163, 86.2%), followed by professional development (*n* = 12, 6.3%), reviews (*n* = 7, 3.7%), commentaries (*n* = 6, 3.2%), and research in brief (*n* = 1, 0.52%. There were 2.94 (*SD* = 1.30) authors per article. There were 19 papers with one author (10.1%), 59 with two authors (31.2%), 56 with three authors (29.6%), 38 with four authors (20.1%), eight with five authors (4.2%), seven with six authors (3.7%), and two with eight authors (1.1%). Table 2 shows the number and type of publications by volume.

Table 2

Number and Type of Publication by Volume

Volume	Total articles	Research	Professional development	Reviews	Commentaries	Research in brief
92	10	6	3	0	0	1
93	8	7	1	0	0	0
94	8	7	1	0	0	0
95	16	15	1	0	0	0
96	21	16	1	2	2	0
97	26	21	0	3	2	0
98	23	20	2	1	0	0
99	23	22	1	0	0	0
100	31	27	2	1	1	0
101	23	22	0	0	1	0

The average number of publications per author was 2.49 (*SD* = 3.68). More than half of the authors had one publication (*n* = 148). There were 14 authors with at least 10 publications, and two of those authors had 24 publications. There were 112 unique first authors from the 189 articles, with a mean of 1.69 (*SD* = 1.41) articles as lead author. Seventy-seven were first author on one publication, and 10 were first author for at least four publications, with two being first author for eight publications. Of the 503 unique coauthor pairs, the mean number of coauthored publications was 1.39 (*SD* = 1.04). The majority (*n* = 399, 79.3%) of coauthor pairs occurred only once. Eleven of the pairs happened at least five times, with 12 being the highest number of interactions between coauthors. The two most prolific authors were responsible for six of the 11 most prolific coauthor pairs.

Objective 2: Describe the Coauthor Network of *JAC* Papers

Table 1 serves as a reference guide for social network analysis terms and definitions. There were 218 nodes in the network, making up 14 components (i.e., subgroups of nodes unconnected to each other). They ranged in size from 2 to 180 nodes. There were 38 nodes outside the largest component. Within the main network, the diameter (i.e., longest of any of the shortest paths between nodes) was seven. There were 32,324 shortest paths in the network, and the average shortest path length was 3.62 for all nodes. The average number of neighbors (i.e., total coauthors of a single author) was 4.61. Network centralization scores can range from 0 to 1, with 1 being the most connected and 0 being the least (Dong & Horvath, 2007). This network centralization was .14, indicating a decentralized network. Network density was 0.02, indicating low connectivity.

Each node represents an author. Each edge represents a link between authors via a coauthored article. There are four parameters visually represented as spectrums in the network. For more detailed descriptions of these terms please see Table 1. Figures 1 visually represents the social network further described in the remaining tables. In the image, the node size is related degree, which is the number of edges connected to the node (Scott, 2017), with larger nodes having higher degrees. The color of the node represents betweenness centrality, which refers to connecting nodes that would otherwise be unconnected (Scott, 2017). Red is low, indicating the node does not connect unconnected nodes, while green is high, indicating the node connects otherwise unconnected networks. Edge size indicates interactions or relationship between nodes, with a larger size indicating more connections (i.e., more coauthored articles). Edge color represents edge betweenness, which refers to "the number of the shortest paths that go through an edge" (Lu & Zhang, 2013, para. 1). Red indicates high edge betweenness, and green is low. In other words, an edge acting as the shortest path between the most nodes would be the reddest. For all spectrums, yellow indicates the in-between amount.

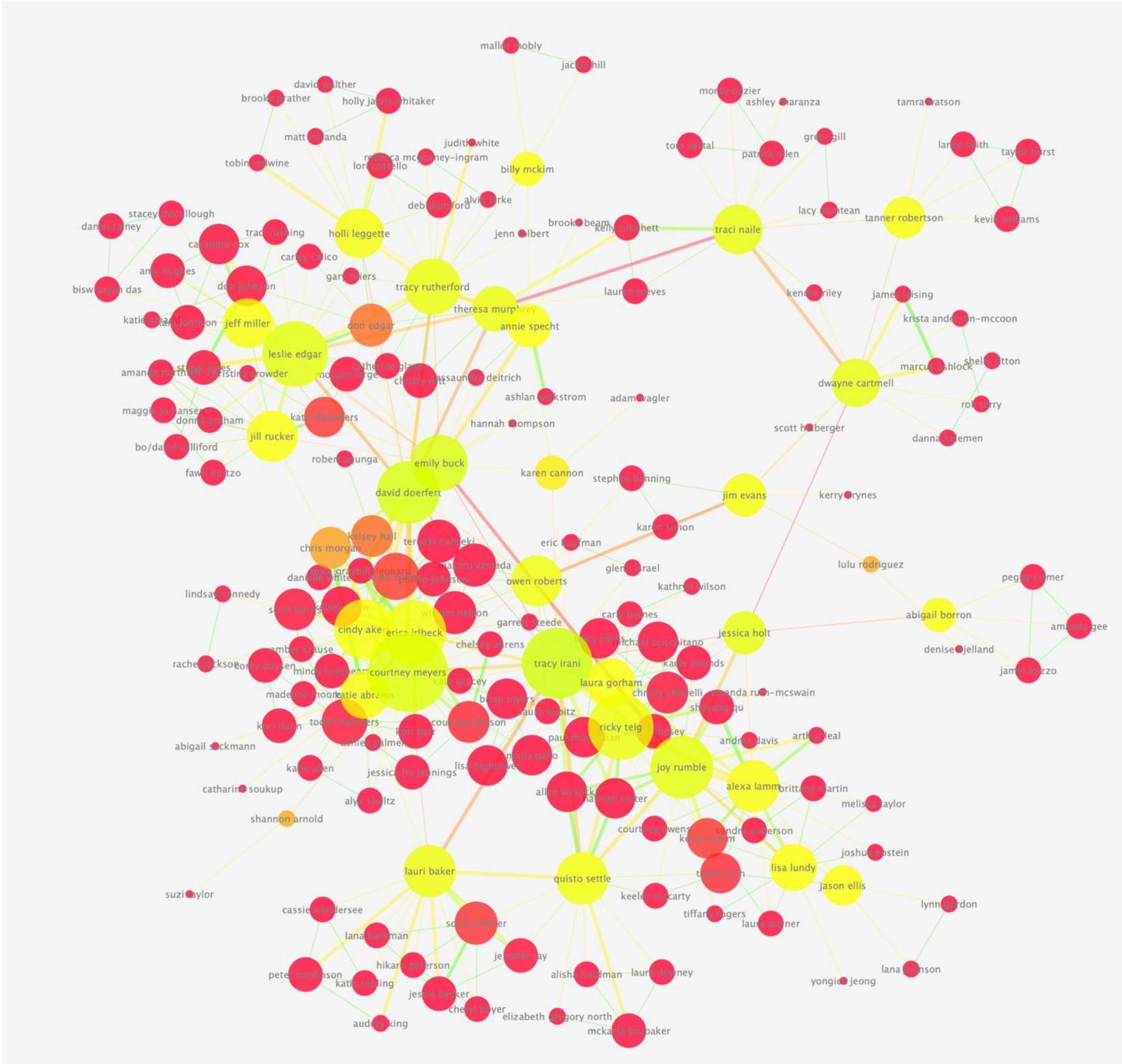

Figure 1. Visual representation of the *Journal of Applied Communications* coauthor main component from 2008-2017.

The betweenness centrality for nodes ranged from 0 to .24 and the mean was .02. Betweenness centrality indicates the extent to which authors connect other authors who would not be otherwise be connected. The clustering coefficient for nodes ranged from 0 to 1. The average clustering coefficient for all nodes was .71. The clustering coefficient shows the extent to which an author's coauthors publish with one another. The average eccentricity score for each node (i.e., node farthest away from them in the network) was 4.95 for the full network. Eccentricity for the entire network ranged from 1 to 7.

Table 3 shows the characteristics of nodes with the most degrees (i.e., connections to other authors). Eight authors have more than 20, with the highest being 35 by Courtney Meyers. Among the most-connected authors, the overall average shortest path length is 2.83, with 2.32 for Tracy Irani having the shortest average path to connect to other authors in the network. The betweenness centrality mean for the most connected authors was .10, with Irani having the highest score at .24. The average clustering coefficient was .21 for the most-connected authors. Dwayne Cartmell had the lowest clustering coefficient among the most-connected authors with .09. For the most-connected authors, three had an eccentricity (i.e., longest of their shortest paths to other authors in the network) score of 4: Irani, David Doerfert, and Owen Roberts.

Table 4 displays the 20 most connected authors and their academic lineage. All institutions of employment after completing their terminal degrees during the period of study are listed. Eight received their terminal degrees from University of Florida (UF). There were five with terminal degrees from Texas A&M University and four from Texas Tech University (TTU), with one person having their degree from both. Irani was the advisor of five of the other most-connected authors. Rutherford and Cartmell were the only others to advise more than one of the other most-connected authors, advising two each. Five of the authors worked at UF after receiving terminal degrees during the timeframe of the study, while four worked at TTU, three worked at University of Arkansas, and three worked at Oklahoma State University.

Table 5 shows the interactions and edge betweenness scores for the 20 coauthors pairs with the most interactions. The average number of interactions between all coauthor pairs was 1.4. The highest was 12 between Irlbeck and Meyers. The mean edge betweenness between all coauthor pairs was 233.03 for the full network. For the pairs with the most connections, the mean was 385.56, with the highest score between Doerfert and Meyers at 1101.61.

Objective 3: Describe the Relationship Between Publication Frequency and Social Network Characteristics of Authors

Correlations were conducted to examine the relationships between the number of publications an author produced and the network characteristics. Most notably, the degree, or number of connections, was strongly related to number of publications ($r = .908$). Betweenness centrality was also strongly related to the total number of publications ($r = .681$). Clustering coefficient, or the connectedness of an author's connections, was moderately related to total number of publications ($r = -.428$). Average shortest path length ($r = -.101$) and eccentricity ($r = .013$) did not have a statistically significant relationship with the number of articles published.

Table 3

Characteristics of Nodes with the Most Degrees

Name	Degree	Average Shortest Path Length	Betweenness Centrality	Clustering Coefficient	Eccentricity
Courtney Meyers	35	2.50	.16	.15	5
Tracy Irani	28	2.32	.24	.15	4
Leslie Edgar	24	2.74	.13	.15	5
Ricky Telg	24	2.67	.10	.18	5
Erica Irlbeck	23	2.72	.07	.18	5
David Doerfert	22	2.41	.20	.25	4
Joy Rumble	22	2.63	.15	.18	5
Cindy Akers	20	2.92	.04	.26	5
Tracy Rutherford	17	2.79	.10	.17	5
Emily Buck	17	2.50	.20	.13	5
Quisto Settle	14	3.05	.07	.23	5
Lauri Baker	14	2.97	.10	.20	5
Alexa Lamm	14	3.08	.04	.24	5
Owen Roberts	13	2.63	.08	.38	4
Jill Rucker	13	3.11	.03	.23	6
Holli Leggette	12	2.98	.06	.24	5
Traci Naile	12	3.39	.11	.14	5
Jefferson Miller	12	3.17	.04	.29	6
Laura Gorham	11	2.87	.03	.35	5
Dwayne Cartmell	11	3.27	.13	.09	5
Katie Abrams	11	2.75	.04	.31	5

Table 4
Institutions and descriptions of highest degree authors

Name	Institution of Terminal Degree and Year of Completion	Institutions of Employment	Degrees Offered at Program of Employment	Doctoral Advisor
Meyers	University of Florida, 2008	Texas Tech University	Bachelor's, Master's, Doctoral	Irani
Irani	University of Florida, 1999	University of Florida	Bachelor's, Master's, Doctoral	Michael Weigold
L. Edgar	Texas A&M University, 2007	University of Arkansas	Bachelor's, Master's	Rutherford & Gary Briers
Telg	Texas A&M University, 1995	University of Florida	Bachelor's, Master's, Doctoral	Carolyn Clark
Irlbeck	Texas Tech University, 2009	Texas Tech University	Bachelor's, Master's, Doctoral	Akers
Doerfert	Ohio State University, 1989	Texas Tech University	Bachelor's, Master's, Doctoral	Kirby Barrick
Rumble	University of Florida, 2013	University of Florida	Bachelor's, Master's, Doctoral	Irani
Akers	Texas Tech University, 2000	Texas Tech University	Bachelor's, Master's, Doctoral	Paul Vaughn & Billy Askins
Rutherford	Texas A&M University, 1998	Texas A&M University	Bachelor's, Master's, Doctoral	Christine Townsend
Buck	University of Florida, 2006	Ohio State University	Bachelor's, Master's, Doctoral	Irani
Settle	University of Florida, 2012	University of Florida, Mississippi State University, Oklahoma State University	Bachelor's, Master's, Doctoral	Telg
L. Baker	University of Florida, 2011	Kansas State University	Bachelor's, Master's	Irani
A. Lamm	University of Florida, 2011	University of Florida	Bachelor's, Master's	Glenn Israel
Roberts	Texas Tech University & Texas A&M University, 2010[a]	University of Guelph	Bachelor's, Master's, Doctoral	Doerfert & Gary Wingenbach

Name	Institution of Terminal Degree and Year of Completion	Institutions of Employment	Degrees Offered at Program of Employment	Doctoral Advisor
Rucker	Oklahoma State University, 2010	University of Arkansas	Bachelor's, Master's	Cartmell
Leggette	Texas A&M University, 2013	Texas A&M University	Bachelor's, Master's, Doctoral	Rutherford
Naile	Oklahoma State University, 2009	Oklahoma State University	Bachelor's, Master's, Doctoral	Cartmell
J. Miller	Oklahoma State University, 2001	University of Arkansas	Bachelor's, Master's	Kathleen Kelsey
Gorham	Texas Tech University, 2017	University of Kentucky	Bachelor's, Master's, Doctoral	Meyers
Cartmell	University of Missouri, 2001	Oklahoma State University	Bachelor's, Master's, Doctoral	James Dyer
Abrams	University of Florida, 2010	University of Illinois, Colorado State University	Bachelor's, Master's, Doctoral[b]	Irani

[a]Degree awarded through the Doc at a Distance Program, which awards degrees from both institution.
[b]A doctoral degree is not available at University of Illinois' agricultural communications program.

Table 5
Coauthor Pairs with Highest Number of Interactions

	Interactions	Edge Betweenness
Irlbeck-Meyers	12	143.13
Lamm-Rumble	8	339.03
Abrams-Meyers	7	129.75
Doerfert-Meyers	7	1101.61
Irani-Rumble	7	725.01
Edgar-Rutherford	6	301.20
Irani-Telg	6	288.31
Irani-Settle	5	951.08
Doerfert-Irlbeck	5	500.15
Rumble-Telg	5	382.49
Baker-Stebner	4	178.03
Rumble-Ruth	4	201.19
Lamm-Qu	4	29.83
Rumble-Settle	4	602.67
Buck-Specht	4	546.78
Akers-Irlbeck	4	141.40
Akers-Meyers	4	276.33
Chambers-Meyers	4	166.83
Edgar-Johnson	4	235.01
Lamm-Telg	4	471.28

Conclusions

In this study, data from *JAC* were used to describe the authorship, category, and frequency of publications from 2008 to 2017 and the social network of the agricultural communications academic community from that time period. Previous research studied the authorship, category and frequency of *JAC* articles from 1990 to 2006 (Naile et al., 2010). Substantial changes can be seen between the time periods. From 1990-2006, 73.6% of articles in *JAC* were categorized as research (Naile et al., 2010), while 86.2% were research articles from 2008-2017. Coauthorship and collaboration became more common during this time period, with single-authored publications reduced from more than half in the Naile et al. study to 10.1% in the current study. Overall, the journal seems to be moving toward more collaborative and research-based articles.

Though the connectedness within the agricultural communications network varies, some patterns emerged. First, individuals who were associated with larger programs, (i.e., greater number of faculty and students in agricultural communications) tended to be more prolific and more connected. It might be that mentoring graduate students is also associated with more connections. Second, collaborating with other faculty, typically at one's current institution, was also associated with more connections. Third, many of the most prolific authors were early in their careers. This could reflect an incentive to publish early in one's career. Furthermore, individuals who went to graduate school together and had the same advisor were common collaborators.

The most prolific coauthor pairs were all colleagues at the same institution at some point prior to the time of publication. By leveraging resources and time together at one institution, authors appear to be more productive. These types of connections would likely be considered strong ties. These ties may result in less new information than weak ties would, but strong ties are more effective at sharing information quickly and have higher levels of trust (Fritsch & Kauffeld-Monz, 2010). Strong ties are more likely to offer critical appraisals of a peer's work (Levin & Cross, 2004). This is especially important in academic research.

Based on the productivity of certain author pairings, most notably two most prolific coauthor pairs, hiring more than one assistant professor in a close timeframe at an institution can help foster productivity and collaborations, though it is not a guarantee of success. If these connections are new at the point of hiring, they could be considered weak ties for a period of time. The strength of ties increases as length of relationship, emotional intensity, and reciprocal actions increase (Granovetter, 1973).

Collaborations within institutions, but different departments, can also be leveraged. For example, Meyers at Texas Tech University collaborates with faculty from the journalism and creative media industries department, as evidenced through the Todd Chambers-Meyers coauthor pairing. Through this collaboration, more resources are able to be leveraged, therefore creating social capital (McFadyen et al., 2009). Relationships with other academic departments are likely to be weaker than within an academic department, but those connections are more likely to foster new information being exchanged within the agricultural communications sector.

The connectivity of an individual in the network could be influenced by a number of factors. For instance, Irani, Doerfert, and Buck have the highest scores of betweenness centrality in the network (i.e., they help connect people who would otherwise be unconnected). This could be attributed in part to their full-time faculty status for the entirety of the analyzed time period, which allows more time for collaborations, especially with graduate students.

The clustering coefficient characteristic of the network offers some insights. Cartmell has the lowest clustering score of the entire network, meaning the nodes Cartmell is connected to are not as well connected to each other. This could be partially attributed to the number of doctoral advisees he collaborated with during the 10-year span who became faculty at other institutions. While Buck has the next lowest score, she has not mentored the same number of graduate students but is a connector to many institutions beyond her own, Ohio State University. Buck served as a connector between personnel at Ohio State, Kansas State University, University of Arkansas, University of Florida, Texas A&M University, University of Nebraska, and Texas Tech University. The wider ranging ties of Cartmell and Buck could be considered weak ties or bridge links. This type of tie is important in social networks and the "information flowing through them can play a crucial role for individuals and for the system" (Rogers, 2003, p. 340).

Connectivity and productivity may also be influenced by the appointment of each person. For example, individuals with higher research appointments would presumably have more time to dedicate to research than individuals with higher teaching or outreach appointments. Faculty with research appointments are allotted dedicated time for research, while faculty with 100% teaching appointments are also expected to publish research without the same time allotment. However, information regarding appointment splits is not readily available and would require further investigation.

The strong correlation between degree centrality and number of publications indicated authors with more connections were more productive. Furthermore, the relationship between total number of publications and betweenness centrality indicates the more publications an author has, the more the author connects otherwise unconnected authors. The negative relationship between clustering coefficient and number of publications shows that the more connected an author's connections are to each other, the lower the number of total publications created by that author.

The results indicate more prolific individuals are connected to a wider variety of individuals than other authors, indicating the value of social capital.

When examining the network as a whole, homophily of some level is evident. In this study, it is evident working in the same department increases the likelihood one will coauthor with a local colleague. Former graduate school colleagues are also likely to be found near one another in the cluster. There are also smaller clusters that are well connected within their own subgroups but do not connect to the larger group as a whole. There is evidence that there is room for increased connections beyond existing institutional ties.

Authors who return to the same relationships to publish have the opportunity to become more efficient and productive (Yang et al, 2017). The longer people work together, the more they learn about each other and are able to play to one another's strengths. While this offers benefits to the individual, the discipline as a whole would benefit from expanding author networks, refreshing ideas, and expanding methodological approaches (Yang et al., 2017).

Table 6 shows how the results of this study compared to other disciplines. Results for agricultural communications were comparable to other social sciences in terms of authors per paper and papers per author, but natural sciences tended to feature more authors per paper and more papers per author, which could be a function of publishing norms varying across disciplines. The clustering coefficient for agricultural communications was relatively high but not the highest compared to all others. The diameter of the network was the smallest of all the networks with that information available, indicating agricultural communications is a comparatively small discipline.

Table 6
Agricultural communications connectivity indicators compared to other fields

	Mean papers per author	Mean authors per paper	Clustering coefficient	Diameter
Agricultural Communications	2.49	2.94	0.710	7
Strategic Management	0.88	1.13	0.130	-
Management and Organization	2.04	1.88	0.680	-
Biomedical	6.40	3.75	0.066	24
Tourism and Hospitality	1.10	1.87	0.748	19
Computer Science	2.60	2.22	0.496	31
High Energy Physics	11.6	8.96	0.726	19

Recommendations

Research

This study represents the first attempt at quantifying and defining collaboration in the field of agricultural communications, so there are opportunities for expanding beyond this baseline data. One limitation of the research was that only *JAC* articles were analyzed. Future research could look at other forms of collaboration and interaction between agricultural communications personnel, such as outreach and teaching collaborations, as well as expanding to non-*JAC* publications. This study assessed if people were connected, not the quality of those connections, which is another limitation. Qualitative research could help understand how connections begin and can be fostered to benefit all researchers involved. There is a possibility two people can be connected without the relationship being viewed as mutually beneficial.

Future studies should explore the relationships between various indicators of connectivity and the influence of circumstances such as geography, academic rank, number of fellow faculty, and number of graduate students mentored. Moreover, co-citation network analysis, a formal clique analysis, and a repeat social network analysis are recommended.

Co-citation network analyses study the articles cited in published articles. This helps to track the progression of disciplines, the formation and building of theory, and research topics. A clique analysis could be beneficial for the discipline. By analyzing cliques further, one could discover the norms, working styles, and hierarchy of each clique. This could help analyze how social capital is exchanged within and between cliques in the full network.

Pairing clique analysis with research like the Baker and King (2016) study that assessed which theories were being used in the discipline could help illustrate how knowledge is collecting and spreading through the agricultural communications discipline. It is also recommended this study be repeated in 10 years to assess changes in the discipline. Moreover, a time series analysis could show network changes over time.

Practice

While there has been an increase in coauthorship, there is still room for growth in collaboration. The bulk of collaborations appeared to be based on shared institutions and academic lineage, while evidence of collaborations based on shared research interests was lacking. For the purpose of distributing social capital across the agricultural communications discipline, it is recommended academicians attempt to collaborate more with people who share their research interests outside of their current and past institutions. This could help ensure research expertise and resources are not siloed at a handful of institutions. Of the 20 most-connected authors, more than half were located at three institutions, despite there being at least 40 agricultural communications programs in the country (Miller et al., 2015).

Practical suggestions for authors depend upon individual goals. If one strives to be a prolific author in *JAC,* based on these data, collaborating with colleagues at one's institution and mentoring graduate students appears to be the best route for success. Results also indicate that productivity is tied to the number of connections of an author, and the diversity of those connections. If one aspires to be the most connected person in the network, connecting with researchers at other institutions and mentoring doctoral students who will become faculty at other institutions is recommended. There is a limited amount of data, but from an institutional perspective, hiring two assistant professors near the same time could help foster productivity and collaboration within a department, though this does not guarantee success, especially if the two faculty members are not willing to collaborate with each other.

Agricultural communications is a relatively small academic discipline, therefore the ability to leverage and build social capital within the academic community is important. In order to leverage and build social capital within the networks, researchers need to continue to network and build connections between institutions. Between conferences and online activities, there is ample opportunity to build these connections, and explore the possibility of research collaborations. As the academic community of agricultural communications continues to grow, increased collaborations have the ability to increase social capital, which creates a shared resource from which all programs benefit.

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