An Application of Social Network Analysis to Focus Group Discussions: Unobserved Interaction between Participants and Discussion Topics

Yu-Lun Wu[1], Joy N. Rumble[2], Taylor K. Ruth[3], Alexa J. Lamm[4], Jason D. Ellis[5]

Abstract

While focus group discussions have become popular across the communication research field, some researchers have pointed out the importance of studying group interactions within focus groups. However, most researchers used a qualitative approach and mostly explored the interaction between participants or between participants and the moderator. This study claimed there might be a third and unobservable interaction that occurs between participants and structured discussion topics. An affiliation network in social network analysis was applied to investigate this phenomenon among eight groups of existing focus group conversations. By affiliation network data and network visualization, this study demonstrated diverse structures between groups. The interaction between participants and discussion topics was significantly different between at least two groups. The results showed that social network analysis could be a tool to help examine focus group interactions from qualitative data, and the interaction between participants and discussion topics could be a potential third interaction in focus group studies. This study is limited by comparing the mean difference between groups. Future research may examine short- and long-term causal effects of group interaction on participation or attitude changes after focus group discussions.

Keywords: focus group; interaction; affiliation network; social network analysis

Introduction

Focus group discussions have become a popular research method across various academic and applied research areas and provided researchers the opportunity to observe how people interactively construct, express, defend, and modify their opinions within a group discussion (Wilkinson, 1998). The

---

[1] Yu-Lun Wu is a PhD Candidate of Agricultural Communication in the Department of Agricultural Communication, Education, and Leadership at The Ohio State University, 200 Agricultural Administration Building, 2120 Fyffe Road, Columbus, OH 43210, wu.3363@osu.edu;

[2] Joy N. Rumble is an Assistant Professor of Agricultural Communication in the Department of Agricultural Communication, Education, and Leadership at the Ohio State University, Halterman Hall 089C, 1328 Dover Rd, Wooster, OH 44691, rumble.6@osu.edu;

[3] Taylor K. Ruth is an Assistant Professor of Agricultural and Environmental Sciences Communication in the Department of Agricultural Leadership, Education, and Communication at the University of Nebraska-Lincoln, 218 Filley Hall, PO BOX 830947, Lincoln, NE 68583-0947, taylor.ruth@unl.edu;

[4] Alexa J. Lamm is an Associate Professor and Extension Evaluation Specialist in the Department of Agricultural Leadership, Education and Communication at the University of Georgia, 318 Hoke Smith Building, Athens GA 30602, alamm@uga.edu;

[5] Jason D. Ellis is a Professor of Agricultural Communications and Journalism and Head of the Department of Communications and Agricultural Education at Kansas State University, 301C Umberger Hall, Manhattan, KS 66506, jdellis@ksu.edu.

method can reveal how individuals feel and think about specific issues and how groups of individuals think differently (Rabiee, 2004). It is also a general research methodology that researchers use to collect data from students, teachers, farmers, or consumers related to agricultural issues. However, focus group methodology, and the possibility of group conformity is often seen as a concern among researchers (Morgan, 1998; Shaw et al., 2015).

A few studies have focused on how group structure within focus groups forms and how it influences communication outcomes. Duggleby (2005) and Wilkinson (1998) pointed out that group interactions in focus groups have been underused and underreported. If we examine the discussion process closer, a constructed social context, an interactive process in which participants can exchange and debate with each other, is found embedded within focus groups (Duggleby, 2005). It is undeniable that participants are situated in an interactive social group, and social interaction forms throughout the discussion. Lunt and Livingstone (1996) stated that focus groups are "socially situated communication" (p. 79) with diversity and variation existing within or between groups. Acocella (2012) suggested that two common interactions occur during the discussion process: interaction between the moderator and the participants and the interaction among participants. However, focus group discussions are structured and directive (Acocella, 2012), and, surprisingly, studies have seldom investigated the interaction between the participants and discussion topics.

Studying group effects in a focus group setting provides an opportunity to see how participants share and make sense of their thinking and experiences (Wilkinson, 1998). Duggleby (2005) reviewed and stated that descriptive qualitative analysis had been most commonly used to analyze interactions among focus participants, while a quantitative approach was seldom conducted. This study explores if social network analysis (SNA) techniques could be applied to focus group discussions. We focus on the interaction between discussion topics and participants to understand participant influences and assess the presence or absence of group conformity. This proposed process may become an integral component of the research process and useful to communications scholars.

Unobserved Interaction in Focus Groups

Focus groups are a popular technique for gathering qualitative data across different social science disciplines. According to Morgan and Spanish (1984), a focus group is defined as "a video- or audio-taped small group discussion that explores topics selected by the researcher and is typically timed to last no more than two hours" (p. 254). Participants are led by a moderator under a structured discussion framework and respond to the topic if they have something to say (Rabiee, 2004). The discussion's content is collected, transcribed, and analyzed in detail, but mostly qualitatively (Acocella, 2012; Morgan & Spanish, 1984).

Focus groups provide insights about how individuals think and feel toward certain issues, also indicating the differences between groups of individuals (Rabiee, 2004). Compared with other research methods, Morgan and Spanish (1984) stated that focus groups are particularly suitable for revealing unexpected or little-known social phenomena. Thus, focus group discussions have been reconsidered and applied across several fields (Wilkinson, 1998).

Discussion is the feature of focus group studies. To collect data from participants, the moderator announces a discussion topic and waits or encourages participants to respond (Acocella, 2012). In this situation, group interactions emerge under a moderator's instruction (Morgan, 1996). Acocella (2012) suggested that two kinds of interactions are likely to occur: 1) the interaction between the participants and the moderator, where the moderator raises a topic and participants to respond to it; and 2) the interaction among participants, like participants asking each other questions, exchanging ideas, and commenting on others' experience or opinions.

Onwuegbuzie et al. (2009) suggested the interactions that occur within focus groups can generate essential data. Understating focus group interactions could allow participants to freely discuss

problems and solutions more (Duggleby, 2005) and offer spontaneous responses (Butler, 1996). In other words, a structured focus group forms an interaction process that could also help participants express their personal thoughts. Although interactions are apparent in focus group discussions, these interactions' nature and influence have been seldom studied (Duggleby, 2005; Kitzinger, 1994; Wilkinson, 1998).

Duggleby (2005) stated that researchers might discover group interaction data in transcripts and observations that were collected from field notes. To study the group interaction, Duggleby (2005) and Halkier (2010) proposed to report the description of the interactions, provide detailed data excerpts, reflect on the study's purpose, or conduct the concept of theoretical sensitivity. Halkier (2010) also reviewed and suggested four different analysis tools: 1) Goffman-inspired interaction analysis, which focuses on how people sustain their narratives in social interaction and regards conversation as a social ritual under the local contextual frame; 2) conversation analysis, which assumes that the content that is interpreted by the participants is influenced by the order and structure of conversations; 3) discourse psychology, which is similar to conversation analysis but analyzes the conversation beyond its situation and social performances; and, 4) positioning theory, which reveals the situational frame of interaction that involves identification and normativity. The above four suggested analysis tools are all qualitative approaches.

Understanding group interactions generated during focus group discussions is critical to research outcomes. While previous studies have pointed to this issue and have assessed it through qualitative approaches (Halkier, 2010; Kitzinger, 1994; Morgan, 2010; Rabiee, 2004; Warr, 2005), this study assumed that social network analysis techniques may provide us the opportunity to utilize quantitative analysis to explore these group interactions that were documented in qualitative textual data. According to Luke (2015), network science has been widely used to study and understand interactions across fields of biological, physical, social, and informational systems by using functions of visualization, network features, participant details, or statistical models. This knowledge can provide a baseline understanding of what interactions are occurring (Settle et al., 2020). The development of several specific software tools and analysis packages allows researchers to solve dynamic and structural network problems in their research (Knoke & Yang, 2008). This study aimed to examine the interaction between discussion topics and participants, while previous research has focused on the interaction between the moderator and participants and the interaction among participants (Acocella, 2012). The purpose of this study was to apply SNA to examine the relationships between participants and topics during focus group discussions. The following research objectives drove the study:

1. Describe specific characteristics of each network structure;
2. Visualize networks in each focus group discussion; and
3. Determine whether interaction existed differently between focus group discussions.

Methods

Case Description

The case we used in this research was part of a larger study that focused on United States consumers' acceptance of biological technologies to combat citrus greening (Rumble et al., 2018; Rumble et al., 2020; Ruth et al., 2019). A third-party company recruited citrus-consuming American residents to join a focus group discussion, which considered participants' age, gender, income, ethnicity, and what their citrus purchasing habits were (Ruth et al., 2019). Before and after the focus group discussions, all participants were asked to take a survey of trust in science, which was adapted from a scale developed by the National Science Board (2018). In the previous study (Rumble et al., 2020), the results showed that participants' trust in science did not sustain throughout the focus group conversations, although the difference was not significant. This study assumed that there might be some unobserved interactions within focus group discussions, which we may seldom consider in research design.

The participants were adult and experienced consumers who resided in four regions of the United States chosen by the researchers. Two focus groups were completed in each region, for a total of eight focus groups. There were 18 participants in Florida, 16 in California, 16 in Illinois, and 23 in New Jersey. A total of 73 individuals participated in the focus group discussions. Most groups were able to meet the balanced representation of males and females, a variety of ages (18 and older), income and education levels, and a variety of races and ethnicities. The demographic data can be found in Table 1.

Table 1

Description of Participants

Characteristic	Apopka, FL ($n = 18$) f	Irvine, CA ($n = 16$) f	Chicago, IL ($n = 16$) f	Princeton, NJ ($n =23$) f	Total ($n = 73$) f
Age					
1-24	0	1	1	1	3
25-34	4	5	6	5	20
35-44	3	4	5	4	16
45-65	11	4	4	12	31
65+	0	2	0	1	3
Gender					
Female	10	7	8	16	41
Male	8	9	8	7	32
Education					
High School	1	3	1	0	5
Some College	9	7	4	7	27
Undergraduate	5	6	10	11	32
Graduate/ Professional School	3	0	1	4	8
Income					
$25,000 >	0	1	0	0	1
$25,000 -$50,000	5	5	3	2	15
$51,000 -$75,000	6	1	4	11	22
$75,000+	7	9	9	9	34
Race/Ethnicity					
White	9	4	10	12	35
African American	2	3	1	7	13
Asian	0	2	0	3	5
Hispanic	7	7	4	0	18
Mixed Race	0	0	1	0	1

Two moderators participated in this study. Moderator 1 led two focus group discussions in New Jersey, while moderator 2 led the rest six focus groups in the other three states. Each focus group discussion lasted 90 to 120 minutes and was guided by a moderator. The discussion was audio-recorded and noted to capture the data (Rumble et al., 2020). The moderator's guide was reviewed by a panel of experts and consisted of eight different discussion topics, which were:

- Group introduction and discussion on a certain agriproduct (1)
- Discussion on agriproduct's disease (2)
- Discussion on the first potential treatment of agriproduct's disease (3)
- Discussion on the second potential treatment of agriproduct's disease (4)
- Discussion on the third potential treatment of agriproduct's disease (5)
- General discussion on all three potential treatments (6)

- Social media message test 1 (7)
- Social media message test 2 (8)

The numbers listed above were used to represent the discussion topics to visualize the interaction between participants and discussion topics in the following network analysis.

Data Collection

A total of 73 participants were recruited in eight focus groups, and they were instructed to discuss the eight previously described discussion topics. This study counted the times that participants expressed distrust in each discussion topic and used the number to simulate the interaction between participants and discussion topics. In the previous study (Rumble et al., 2020), the codes of trust and distrust were used to analyze transcriptions, and distrust codes were found throughout the focus group transcripts, which appeared five times more than trust codes (Rumble et al., 2020). Distrust codes included:

1. Lack of information: Not enough information or too many questions left unanswered;
2. Skepticism: Feeling some information was withheld, not transparent or honest;
3. Fear: Scary, or related to similar historical events; and
4. Lack of benevolence: Feel like science is all for increasing profits; consumers' concerns will not be considered.

Analysis

An affiliation network in the social network analysis can analyze the interaction between participants and discussion topics, which is used to express how the participants are related to one another in a subgroup (Luke, 2015). "Affiliations" in social network analysis usually indicates "membership or participation data" (p. 417) that it assumes that a group's co-membership is a possible indicator of a social tie (Borgatti & Halgin, 2014). The classic example of an affiliation network is the analysis of student structure within a class, revealing how connections are built between students and how subgroups are formed within a class (Luke, 2015). Affiliation network may also be applied to examine the relationship between person and membership, or person and events (Borgatti, 2009).

The data is constituted of "a set of binary relationships between members of two sets of items" (Borgatti & Halgin, 2014, p. 417), which refers to two-mode data, or incidence matrix (Luke, 2015). The incidence matrix is the most critical feature of an affiliation network. It is similar to the adjacency matrix, the most common one-mode data in SNA. The significant difference between the two matrices is that an adjacency matrix is constituted of a square matrix (n×n) between participants and participants, but an incidence matrix is constructed between individuals and groups (n×g), which might be a square or rectangle matrix (Luke, 2015). The data could also be projected into one-mode data to examine how two participants join the same group or event, called co-affiliation (Borgatti & Halgin, 2014). With this approach, we were able to construct the unobserved interaction between participants and discussion topics.

Objectives 1 and 2 are often the first step to examine network data. The network's description was based on the five-number summary, which was developed by Tukey (1977). It includes size, density, component, diameter, and clustering coefficient (Luke, 2015). However, some of the network descriptive, like density, might not be meaningful to describe how the network data were calculated, and not every description is suitable for the affiliation networks (Luke, 2015). This study used participants, node degree, component, diameter, and clustering coefficient to describe each focus group's network feature. A detailed definition of network features, as discussed in Iacobucci (1994) and Luke (2015), is shown in Table 2.

Table 2
Definitions of Basic Network Terminology

Term	Definition
Participant	The number of participants in each focus group.
Node degree	The number of ties it has with other nodes.
Components	The number of connected subgraphs in which all actors are connected.
Diameter	The longest of the shortest paths across all pairs of nodes. If a graph isn't connected, the diameter is undefined.
Clustering coefficient	The number of closed triangles, a measure of transitivity, which ranges from 0 to 1.

Except for the overall network description, it is also important to investigate centrality at the individual level because the network and its members are mutually influenced. As the network structure has an impact on members, how members connect to each other also contributes to the network structure (Luke, 2015). By calculating centrality, we are able to find out the most influential members. There are three common indicators: degree centrality, closeness centrality, and betweenness centrality. However, because there were isolated nodes in this study (participants who did not express distrust among discussion topics), closeness centrality was not used. We chose not to use closeness centrality because this indicator is not well-defined for disconnected graphs. Therefore, this study used degree centrality and betweenness centrality. A detailed explanation of each indicator, as discussed by Borgatti and Halgin (2014), Iacoubucci (1994), and Luke (2015), has been listed in Table 3.

Table 3
Common Measurements of Centrality

Indicator	Definition
Degree centrality	The number of connections a node has with other nodes.
Closeness centrality	The closeness of each node connects to every other node in a network. This measure will not be well-defined for disconnected graphs.
Betweenness centrality	The extent that a node locates between pairs of other nodes in the network.

Both objectives 1 and 2 were conducted in RStudio (Version 1.1.414), while the centrality data in objective 3 were generated by RStudio (Version 1.1.414) first and applied in SPSS® 25.0 to examine whether there were any statistically significant differences between focus groups. Three variables, degree centrality, betweenness centrality, and the times of expressing distrust, were examined across eight focus groups by using one-way ANOVA.

Three specific assumptions were required to meet to conduct a one-way ANOVA: 1) normality, 2) independence, and 3) homogeneity of variance (Lomax & Hahs-Vaughn, 2012). The assumption of normality was tested via the examination of the residuals. Although the S-W test did not meet assumptions for normality ($p < .05$), the histogram, skewness, kurtosis, and Q-Q plot all suggested that normality was a reasonable assumption. Scatterplots of residuals against the levels of the independent variable were reviewed. The random displays of points around zero provided evidence that the assumption of independence was met. However, according to Levene's test, the homogeneity of variance assumption was only satisfied by the times of expressing distrust [$F_{(7, 65)} = 1.898, p = .084$].

Results

Objective 1: Describe Specific Characteristics Of Each Network Structure

As Table 4 shows, the participants of each focus group ranged from eight to 12 people. Most

participants expressed distrust in between four to five discussion topics, as seen in the node degree results. NJ1 participants only expressed distrust in 2.833 discussion topics on average, and IL2 participants expressed distrust in 5.625 discussion topics on average. Components results showed that across all groups, there existed two to four discussion topics that all participants expressed distrust toward. Based on the diameter, it took three to four steps to connect the two nodes, which were the furthest apart in the network. Last, based on the results of the clustering coefficient, some of the groups did not have transitivity (cluster coefficient = 0), while CA1, CA2, IL1, IL2 groups had a higher portion of closed triangles within their own network.
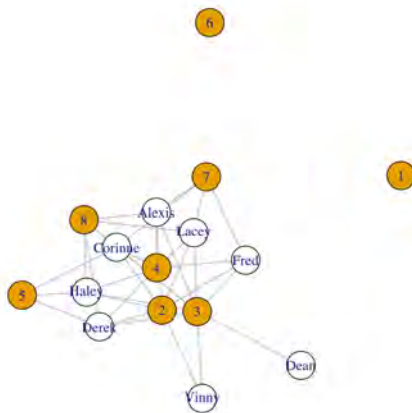
Table 4
Characteristics of Each Network Structure

| Group	Participant	Node degree	Components	Diameter	Clustering coefficient
CA 1	8	4.125	3	3	.821
CA 2	8	4.125	4	3	.836
FL 1	9	4.125	3	4	0
FL 2	9	4.125	3	3	0
NJ 1	12	2.833	3	4	0
NJ 2	11	4.455	3	3	0
IL 1	8	4.375	2	3	.714
IL 2	8	5.625	2	3	.844

Objective 2: Visualize Networks In Each Focus Group Discussion

Each group's network, which was constructed by expressions of distrust, is illustrated in the below figures (Figure 1 to 8). The orange circles represent the eight discussion topics, and the white circles are participants. Some isolated circles indicate no participants expressed distrust for certain discussion topics, or certain participants did not express distrust among all discussion topics in their focus groups. The results showed that different focus groups formed different patterns of group interaction.
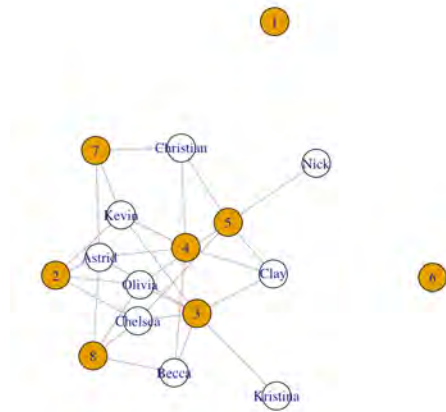
Figure 1   **Figure 2**
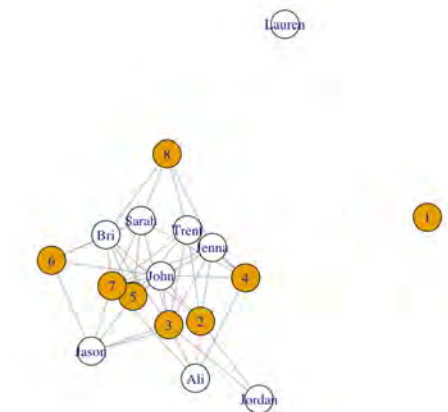*California Group 1*   *California Group 2*
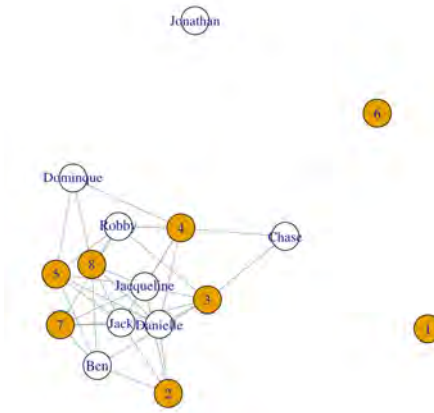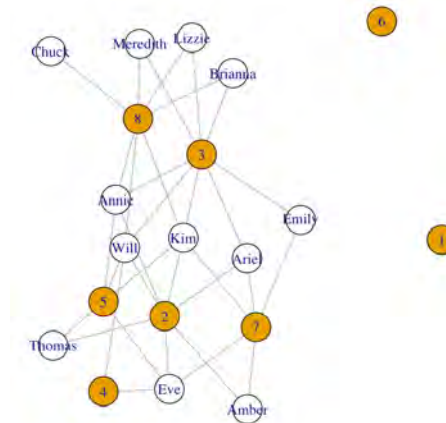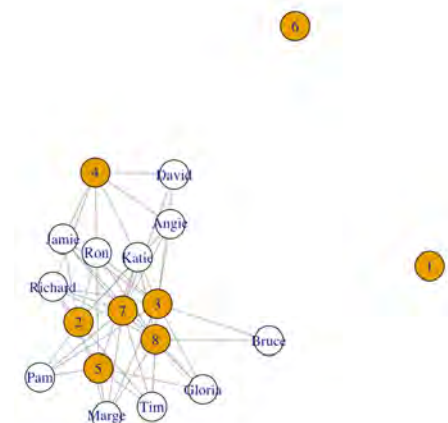
Figure 3
Florida Group 1

Figure 4
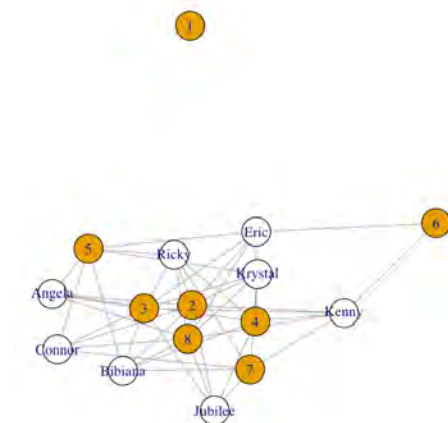*Florida Group 2*

Figure 5
New Jersey Group 1

Figure 6
New Jersey Group 2

Figure 7
Illinois Group 1

Figure 8
Illinois Group 2

Objective 3: Determine Whether Interaction Existed Differently Between Focus Group Discussions

As seen in Table 5, the one-way ANOVA was statistically significant [$F_{(7, 65)} = 2.888$, $p = .011$], the effect size η^2 was .237, which is explained as a large effect based on Cohen (1988), and observed power is strong (.898).

Table 5
Mean Comparison of Times Expressing Distrust Between Focus Groups

Source		SS	df	MS	F	p
Times of	Between Groups	434.922	7	62.132	2.888	.011**
expressing distrust	Within Groups	1398.448	65	21.515		
	Total	1833.370	72			

Because homogeneity of variance assumption was not met, the alternative Welch and Brown-Forsythe tests were applied to examine degree and eigenvector (Table 6). The *p* values indicated there is a statistically significant difference in the mean of degree and eigenvector between different focus groups with a large effect size ($\eta^2 = .237$). How participants connected with each other within groups was not the same between the eight focus group discussions.

Table 6
Robust Tests of Equality of Means

Source		Statistic	df1	df2	p
Degree	Welch	7.872	7	26.428	.000**
	Brown-Forsythe	2.860	7	43.576	.015**
Eigenvector	Welch	5.003	7	26.143	.001**
	Brown-Forsythe	1.597	7	39.210	.165

This study further conducted a Tukey post hoc test to determine which focus group means were significantly different (see Table 7). Using an alpha of .05, the results indicated the average times of expressing distrust in focus group FL1 (*M* = 4.89, *SD* = 3.621) was significantly different than the average times of expressing distrust in focus group IL2 (*M* = 12, *SD* = 2, *t* = -7.111, *p* = .047). The average times of expressing distrust in focus group NJ1 (*M* = 4.42, *SD* = 3.232) was significantly different than the average times of expressing distrust in focus group IL2 (*M* = 12, *SD* = 2), *t* = -7.583, *p* = .014.

Table 7
Multiple Comparisons on Times of Expressing Distrust

(I) Focus group	(J) Focus group							
	CA1	CA2	FL1	FL2	NJ1	NJ2	IL1	IL2
CA1	--	-1.375 (.999)	2.111 (.981)	-.556 (1)	2.583 (.923)	-3.364 (.771)	-1 (1)	-5 (.392)
CA2	--	--	3.486 (.779)	.819 (1)	3.958 (.576)	-1.989 (.983)	.375 (1)	-3.625 (.770)
FL1	--	--	--	-2.667 (.923)	.472 (1)	-5.475 (.166)	-3.111 (.863)	-7.111* (.047)
FL2	--	--	--	--	3.139 (.786)	-2.808 (.877)	-.444 (1)	-4.444 (.508)
NJ1	--	--	--	--	--	-5.947 (.508)	-3.583 (.692)	-7.583* (.014)
NJ2	--	--	--	--	--	--	2.364 (.955)	-1.636 (.955)
IL1	--	--	--	--	--	--	--	-4 (.671)
IL2	--	--	--	--	--	--	--	--

Discussion

The analysis of objectives 1 and 2 showed that different focus groups formed their own group structures based on how they participated in discussion topics, no matter from the network level or individual level. The results of the node degree indicated that focus group IL2 had the highest degree. Complimentary manuscripts might be able to prove that this focus group expressed more instances of "not enough information or too many questions left unanswered" than other groups in this study. The results demonstrated a significant difference between focus groups' frequency of distrust expressions. This finding infers that the unobserved interaction between participants and discussion topics existed differently between focus group discussions. The significant differences of degree and betweenness centrality between groups revealed that how participants connected with each other also existed differently between focus group discussions. In sum, these results have pointed out that unobserved interactions were present within a focus group and performed differently between focus groups. Researchers could utilize this process and results to identify what causes one focus group to differ from the others and to consider when a focus group discussion may need to be treated differently from the others.

From a theoretical perspective, this study pointed to the importance of assessing unobserved interaction in social science research. Based on the results, we may suggest that the unobserved interaction between participants and discussion topics might be a potential variable that may influence the developing process in focus groups. From a methodological perspective, this study demonstrated an example of applying SNA to study existing qualitative data, which may be considered in future focus group discussions or mixed-method designs. From a practical perspective, we have indicated that group interaction may exist in the unobservable situation, which may be indicative of an error in a focus group design. By using SNA, we are able to discover the constructive difference between groups as we compile results and consider the trustworthiness and credibility of data. Future research design could consider documenting and analyzing interactions among participants, between participants and the moderator, and between participants and discussion topics.

This study is limited by comparing the structural difference between groups; the impact of the unobserved interaction on groups or individuals has not been assessed. Ruth et al. (2018) assumed that people's perceived opinions of others, take focus group setting as an example, may have an interaction effect on their willingness to express attitudes toward a specific issue, which may indirectly impact the intent of acceptance or rejection toward the specific issue. Future research may examine short- and long-term causal effects of group interaction on participation or attitude changes after focus group discussions. Because of the limitation of verbal transcription, nonverbal cues may not be documented in the process (Clayman et al., 2009); future focus group research may consider using video-recording for accounting for nonverbal cues and applying SNA with advanced analysis, for instance, dynamic network models. Although this study was exploratory, it offers insight into the power of SNA for application in focus group methodology.

References

Acocella, I. (2012). The focus groups in social research: advantages and disadvantages. *Quality & Quantity, 46*(4), 1125-1136. https://doi.org/10.1007/s11135-011-9600-4

Borgatti, S. P. (2009). 2-Mode concepts in social network analysis. *Encyclopedia of Complexity and System Science, 6*, 8279-8291. https://doi.org/10.1007/978-0-387-30440-3_491 http://www.analytictech.com/borgatti/papers/2modeconcepts.pdf

Borgatti, S. P., & Halgin, D. (2014). Analyzing affiliation networks. In J. Scott & P. J. Carrington (Eds.), *The SAGE handbook of social network analysis* (pp. 417-433). SAGE Publications Ltd.

Butler, S. (1996). Child protection or professional self-preservation by the baby nurses?: Public health nurses and child protection in Ireland. *Social Science & Medicine, 43*, 303–314. https://doi.org/10.1016/0277-9536(95)00378-9

Clayman, M. L., Webb, J., Zick, A., Cameron, K. A., Rintamaki, L., & Makoul, G. (2009). Video review: An alternative to coding transcripts of focus groups. *Communication Methods and Measures, 3*(4), 216-222. https://doi.org/10.1080/19312450903378891

Cohen J. (1988). *Statistical power analysis for the behavioral sciences*. Routledge Academic

Duggleby, W. (2005). What about focus group interaction data? *Qualitative Health Research, 15*(6), 832-840. https://doi.org/10.1177/1049732304273916

Halkier, B. (2010). Focus groups as social enactments: Integrating interaction and content in the analysis of focus group data. *Qualitative Research, 10*(1), 71-89. https://doi.org/10.1177/1468794109348683

Iacobucci, D. (1994). Graphs and matrices. In S. Wasserman & K. Faust (Eds.), *Social network analysis: Methods and applications (Structural analysis in the social sciences)* (pp. 92-166). Cambridge University Press.

Kitzinger, J. (1994). The methodology of focus groups: The importance of interaction between research participants. *Sociology of Health & Illness, 16*(1), 103-121. https://doi.org/10.1111/1467-9566.ep11347023

Knoke, D., & Yang, S. (2008). *Quantitative applications in the social sciences: Social network analysis*. SAGE Publications, Inc.

Lomax, R. G., & Hahs-Vaughn, D. L. (2012). *One-factor analysis of variance fixed-effects model.* Routledge.

Luke, D. A. (2015). *A user's guide to network analysis in R*. Springer.

Lunt, P., & Livingstone, S. (1996). Rethinking the focus group in media and communications research. *Journal of Communication, 46*(2), 79-98. https://doi.org/10.1111/j.1460-2466.1996.tb01475.x

Morgan, D. L. (1996). Focus groups. *Annual Review of Sociology, 22*(1), 129-152. https://doi.org/10.1146/annurev.soc.22.1.129

Morgan, D. L. (1998). *The focus group guidebook*. Sage Publications, Inc.

Morgan, D. L. (2010). Reconsidering the role of interaction in analyzing and reporting focus groups. *Qualitative Health Research, 20*(5), 718-722. https://doi.org/10.1177/1049732310364627

Morgan, D. L., & Spanish, M. T. (1984). Focus groups: A new tool for qualitative research. *Qualitative Sociology, 7*(3), 253-270. https://doi.org/10.1007/BF00987314

National Science Board. (2018). *Science and technology: Public attitudes and public understanding*. Retrieved from https://nsf.gov/statistics/2018/nsb20181/report/sections/science-and-technology-public-attitudes-and-understanding/highlights.

Onwuegbuzie, A. J., Dickinson, W. B., Leech, N. L., & Zoran, A. G. (2009). A qualitative framework for collecting and analyzing data in focus group research. *International Journal of Qualitative Methods, 8*(3), 1-21. https://doi.org/10.1177/160940690900800301

RStudio Team (2020). *RStudio: Integrated development for R*. RStudio, PBC. http://www.rstudio.com/

Rabiee, F. (2004). Focus-group interview and data analysis. *Proceedings of the Nutrition Society, 63*(4), 655-660. https://doi.org/10.1079/PNS2004399

Rumble, J. N., Lamm, A. J., Beattie, P. N., & Ruth, T. K. (2018). *Attitudes and transparency: A case for communication*. Paper presented at the 2018 annual meeting of the Association for International Agricultural and Extension Education, Merida, Yucatan, Mexico.

Rumble, J. N., Wu, Y.-L., Tully, K. M., Ruth, T. K., Ellis, J. D., & Lamm, A. J. (2020). A mixed-methods comparison of self-reported and conversational trust in science. *Journal of Applied Communications, 104*(4). https://doi.org/10.4148/1051-0834.2371

Ruth, T. K., Rumble, J. N., Lamm, A. J., & Ellis, J. D. (2018). A model for understanding decision-making related to agriculture and natural resource science and technology. *Journal of Agricultural Education, 59*(4), 224-237. https://doi.org/10.5032/jae.2018.04224

Ruth, T. K., Rumble, J. N., Lamm, A. J., & Ellis, J. D. (2019). *How consumers contrast and assimilate information about agricultural biotechnology*. Paper presented at 2019 National Agricultural Communications Symposium, Birmingham, AL.

Settle, Q., Teixeira, K., Bechtold, R., Shoulders, C., & King, A. (2020). Coauthor network analysis of journal of agricultural education articles from 2008-2017. *Journal of Agricultural Education, 61*(2), 115-127. https://doi.org/10.5032/jae.2020.02115

Shaw, K., Meyers, C., Irlbeck, E., Doerfert, D., Abrams, K., & Morgan, C. (2015). Agriculturists personal and business use of online communication tools. *Journal of Applied Communications, 99*(2), 15-29. https://doi.org/10.4148/1051-0834.1045

Tukey, J. (1977). *Exploratory data analysis*. Addison-Wesley.

Warr, D. J. (2005). "It was fun... but we don't usually talk about these things": Analyzing Sociable Interaction in Focus Groups. *Qualitative Inquiry, 11*(2), 200-225. https://doi.org/10.1177/1077800404273412

Wilkinson, S. (1998). Focus groups in health research: Exploring the meanings of health and illness. *Journal of Health Psychology, 3*(3), 329-348. https://doi.org/10.1177/135910539800300304