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Social Network Analysis as a Predictor of Communication Patterns in a Small Group

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by

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by

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has been approved

at the

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George Fox University

as a Dissertation for the PsyD degree

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Date: 2. 11. 21

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Abstract

Few studies have examined interdisciplinary collaboration in primary care using social network analysis. The present study seeks to examine connections among leadership in the Interprofessional Primary Care Institute (IPCI) in order to measure the effect of changes in the network over time, effect of work group collaboration, and centralization on communication patterns within the group. This study involved a secondary analysis, using data from Gathercoal et al.'s (2019) social network analysis (SNA) of the IPCI, and follow-up data collection. Data were gathered via an online survey, meeting records, and collateral information about IPCI. Social connections within the network, specifically eigenvector centrality measures, were calculated using the Cytoscape program. Results showed that individuals in two or more workgroups had more incoming comments while individuals in fewer work groups were more likely to send outgoing comments. Individuals with higher centrality at the beginning of the network participated in fewer workgroups. Members' eigenvector centrality did not differ significantly at Time 2 as a function of the number of work groups to which they belonged.

The present study revealed the importance of influence centrality (e.g., eigenvector centrality) and work group involvement in the IPCI network as it relates to the value and communication patterns of its members. SNA is a valuable method to analyze the interworking of interdisciplinary networks to support and enhance collaboration among diverse professionals in the health sector.

Keywords: social network analysis, primary care, interdisciplinary.

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Chapter 1

Introduction

Interdisciplinary Collaboration in Primary Care

Primary care has become a foundational model of healthcare delivery in the U.S. over the last 70 years. The central aim of primary care is to provide greater access to population-based, high-quality healthcare with an emphasis on prevention, efficiency in reducing unnecessary specialty/inpatient care, and early intervention ("History: Major Milestones," 2020). In 2006, the patient-centered medical home model was developed, which led to an increased focus on individualized, quality-controlled care for all primary care patients. As primary care developed, there became an apparent need for developing a more team-based, multi-disciplinary approach to care in order to both decrease physician burnout and improve comprehensive care adequate to address the diverse needs of each patient (Cheong et al., 2013).

Utilization of interdisciplinary teams has been shown to significantly reduce hospitalizations, improve patient health outcomes, increase patient engagement in care, and overall save costs (Cheong et al., 2013). A team-approach utilizes the unique skill set and knowledge of diverse professionals to support the biopsychosocial health of all patients (Oyemaja, 2018). Many clinics have adapted and integrated behavioral health clinicians, team nurses, culturally responsive health workers (CR-HWs), and pharmacists (Oyemaja, 2018). The development of a team approach to primary care shifted the hierarchical approach from relying on one physician to valuing team members' contributions to patient care (Parchmen et al., 2019).

In a systematic review, Mulvale et al. (2016) identified several significant factors for success in interdisciplinary collaboration at a team level including team leadership, size, level of conflict, open communication, supportive colleagues, team vision-goals, group problem solving, team meetings, decision making processes, and feeling part of the team. Additionally, the review highlights the importance of viewing leadership roles as a team champions or facilitators.

Despite the recent shift in primary care towards an integrated model, there remains a significant need for training and implementation of team-based care in primary care practices to include mental health care, case management, and culturally sensitive care. Cheong (2013) presents several interventions to increase interdisciplinary collaboration including collaborative workshops, provision of communication tools in clinic, referral processes, remuneration, and incentive plans.

Interprofessional Primary Care Institute

In 2018, the Interprofessional Primary Care Institute (IPCI) was established in an effort to provide interprofessional training opportunities and innovation in primary care. The IPCI seeks to develop "diverse, optimally-leveraged, interprofessional primary care teams" through continuing medical education for PCCs, BHCs, clinical pharmacists, and nurses as well as to provide intensive events for emerging roles of BHCs and CR-HWs (Oyemaja, 2018). Looking at how IPCI fosters collaboration with-in their own network is relevant as their goal is to promote interdisciplinary collaboration via training and direct modeling in their own board of directors.

Social Network Analysis

Over the last century, social network analysis (SNA) has become a widely used tool to study social networks and small groups (Katz, et al., 2004). In particular, there was a resurgence of popularity of the approach in the 1990s as the ability to quantify and visualize relationship patterns improved. SNA has been used by many fields such as education, sociology, psychology, and business. SNA seeks to describe and analyze a group's key actors (referred to as "nodes") and how all the nodes are connected through relational ties. A connection between two actors in the SNA is known as a "dyad." SNA identifies groups within a network called "cliques" when all actors are equally connected to all other actors in the clique. Subgroups are similar to cliques, but less tightly linked together (Wasserman & Faust, 1994). SNA measures the density of a network. Density refers to the level of linkage within the whole network by measuring the number of connections with the number of total possible connections (Rizzuto et al., 2009).

SNA uses data by collecting ratings from each individual regarding all the other group members. The ratings are used to measure connections and form sociograms. Sociograms are visual representations of the social network nodes and ties. In social networks, there are several important factors which shape the nature of relational ties, including strength, direction, content, and positive or negative quality of the tie. Furthermore, SNA can measure a variety of ways individuals within the network might be connected, including communication ties, formal ties, affective ties, material ties, proximity ties, and cognitive ties. In addition to the types of ties, researchers have created several metrics to define how central or important each actor is within the overall network, including degree centrality, betweenness centrality, closeness centrality, transitivity and eigenvector centrality (Katz et al., 2004).

Each measure of centrality calculates the actors' importance in a different way. For example, degree centrality is the simplest form of centrality and assigns an importance score based simply on the number of links held by each node. Betweenness centrality measures the number of times a node lies on the shortest path between other nodes. Betweenness indicates which actors are bridges to others in the network. Like degree centrality, Eigenvector centrality measures a node's influence based on the number of links it has to other nodes in the network, but then goes on to weight that value based on how many links their connections have (e.g., popularity. Eigenvector centrality can identify nodes with influence over the whole network, not just those directly connected to it.

Research using SNA has demonstrated principles related to the formation of ties between members in networks. The principle of homophily encompasses an individual's tendency to form ties with others who share similar qualities (McPherson et al., 2001). Though similar characteristics can encourage connections, SNA researchers suggest individuals' relational ties as more predictive of behavior than other factors such as identity markers or attitudes (Katz, et al., 2004). Similarly, SNA looks at all relational ties holistically, viewing boundaries and overlap as fluid. Contemporary SNA has shifted from primarily focusing on the units that make up a network to emphasizing relational connections and processes related to outcomes (Sun, 2019).

Communication is an essential component of the relationships and processes in SNA. The public goods theory of SNA suggests communication and subgroup formations often occur in order to work towards a shared goal (Hardin, 1982; Olson, 1965; Samuelson, 1954; as cited in Katz, et al., 2004). When a network works together, communication is essential in developing ties in order to maximize all resources and initiate action. In addition to developing communication ties, the theory of transactive memory highlights the development of communication networks, which allow the network to utilize individuals' skills and knowledge without needing all members to possess the same qualities (Hollingshead, 1998; Moreland, 1999; Wegner, 1987, 1995; as cited in Katz et al., 2004).

SNA Research and Primary Care

Despite the large and growing body of research using SNA, there are relatively few studies aimed at examining social networks in the health sector. Due to the social phenomenon of homophily (the tendency to form connections with individuals sharing the same characteristics), establishing diverse, interdisciplinary networks can be challenging. SNA has been supported as a beneficial tool to study interdisciplinary team functioning and enhancement (Cheong et al., 2013; Cunningham et al., 2011; Ryan et al., 2013). In a systematic review, Cunningham et al. (2011) analyzed 26 SNA studies exploring various healthcare networks in order to identify characteristics leading to improved patient care and sustainability. The results of the systematic review outlined specific network features associated with positive outcomes (e.g., hierarchy in nursing networks, degrees of separation in GP networks). Overall findings support the benefits of collaborative, well-connected networks in healthcare as correlated to better patient outcomes and safety. Results pointed to the importance of centralized key actors in the network as needed for both information transmission and bridging among sub-groups; however, key actors were simultaneously identified as a potential weakness if overly-relied upon (Cunningham et al., 2011).

Within the SNA literature in the health sector, there exists a sparse subset of research in primary care settings. Cheong et al. (2013) explored the patient's role in primary care team networks using a mixed method SNA with asthma patients. The results indicated the vital role of the patient's perspective in the interdisciplinary model and limitations in collaboration of physicians.

The present study uses SNA as a tool to explore interdisciplinary collaboration with-in the IPCI board. The IPCI board of directors presented an opportunity to analyze an interdisciplinary network of leaders as a model of the collaboration they promote in primary care settings. Following the formation of the IPCI, members were asked to join work groups to accomplish various goals of the institute (e.g., facilitating training events). The diversity of disciplines and roles in the health sector among members and variance in work group participation allowed for exploration of interdisciplinary network dynamics.

Hypotheses

Based on the assumption that relational ties would be formed and strengthened with the formation of work groups, the first hypothesis was that work group involvement would be associated with greater social network eigenvector centrality at Time 1 and Time 3. The second hypothesis was that work group involvement would also be associated with increased incoming and outgoing comments on IPCI meeting chat.

Chapter 2

Method

Participants

The participants for this study were Directors of the Interprofessional Primary Care Institute (*n* = 18). Most were women (83.3%), white (67%), and behavioral health clinicians (44%). The director group included physicians, nurses, advanced-practice clinicians, behavioral health clinicians (psychologists), culturally-responsive community health workers, physical therapists, and quality improvement practitioners. They responded in the context of regular director meetings of the IPC Institute.

Measures

Social Network Analysis Survey

Directors were asked to respond to every other Director using a Likert scale to answer the question, “How well do you know _____?” Responses ranges from 1 = *not at all familiar* to 7 = *I know this person very well*.

Chat interactions

During an IPC Institute event remote (zoom) event, the IPC Institute Director asked all the directors to “type in the chat throughout the event your words of encouragement to others. Tell them how they strengthen you, and all of us.” After the event concluded the chat history was downloaded and was made available for this study.

Procedures

The IPC Institute sent out the Social Network Analysis Survey with other preparation materials using an online survey platform before the first Directors' meeting (T1). Directors were asked to respond to the Social Network Analysis Survey again before the third Directors' meeting (T2), which took place a year later. Six months after the second Directors' meeting (T2), a training event, focused on Chronic Conditions Solutions, was held on a zoom platform (T3). Most IPC Institute Directors were present at the Solutions event (T3) and those present were asked to type comments, using the zoom chat function, to encourage others. The prompt was, "Tell them how they strengthen you, and all of us." After the Solutions event (T3), the zoom chat comments were saved in an electronic file.

Chapter 3

Results

The purpose of this study was to explore the extent to which Social Network Analysis measures of eigenvector centrality are predictors of communication patterns for directors of an Interprofessional organization.

Descriptive Statistics

Five variables were selected as foci of this study: the number of incoming comments at Time 3, the number of outgoing comments at Time 3, and two measures of SNA Centrality – eigenvector at Time 1 and eigenvector at Time 2. None of the means of these variables differed significantly as a function of gender (M, F), discipline (BHC versus other), or institution (GFU versus other), so the data were collapsed across these three demographic variables. The number of comments and eigenvector centrality values were affected by the number of work groups in which directors were involved. Table 1 shows the mean values for each variable for directors involved in one work group or several work groups.

Effect Sizes

Due to the small sample size and resulting low power, follow-up effect size analyses were conducted in order to assess the interactions of group and time for the seven dependent variables. Table 2 shows the effect sizes and the confidence intervals for the variables of interest. The calculations were accomplished using an online calculator, located on the Campbell Collaborative site (Wilson, n.d.), Cohen's d' values are interpreted such that values between zero

Table 1

Mean Values for each Variable for Directors Involved in One Work Group or Several Work Groups

	One Work Group			Two or More Groups		
	Mean	*SD*	*N*	Mean	*SD*	*N*
Incoming comments	1.20	0.84	5	4.00	2.77	7
Outgoing comments	3.75	1.26	4	2.29	1.38	7
T1 Eigenvector	0.12	0.23	9	-0.16	0.30	7
T2 Eigenvector	-0.02	0.57	10	0.07	0.17	8

Table 2

Effect Sizes for each Variable for Directors Involved in One Work Group or Several Work Groups.

			95% Confidence			
	d'	size	Lower	Upper	*t*-value	sig
Incoming comments	1.48	Very Large	2.77	0.18	2.52	.04
Outgoing comments	-1.09	Large	0.22	-2.40	-1.74	.12
T1 Eigenvector	-1.06	Large	-0.01	-2.12	-2.11	.05
T2 Eigenvector	0.19	No effect	1.12	-0.74	0.41	.69

and .2 indicate no effect, values between .2 and .5 indicate a small effect, values between .5 and .8 indicate a moderate effect, and values which exceed .8 indicate a large effect. A positive effect size value results if the mean for those involved in more groups is larger while a negative value results if those involved on only one work group had a larger mean. The 95% Confidence Interval (CI) of the Effect Size is dependent upon sample size, such that the smaller the sample size, the broader the span of the confidence interval. If the 95% Confidence Interval (CI) spans across zero, then the d' values is not considered reliably different from "no effect." Table 2 displays the effect sizes for the variables of interest. Very Large and large effects are noted for Incoming comments, Outgoing comments, and Time 1 Eigenvector Centrality values, although it should be noted that for Outgoing comments the 95% CI indicates this effect is not reliable.

Predicting Conference Chat Interactions

Multiple regression was used to determine whether the number of incoming and outgoing comments during a conference at Time 4, could be predicted using the measures of SNA Centrality – Eigenvector at Time 1, Eigenvector at Time 2, as well as the number of work groups in which each director was active (range 1 – 4; Mean = 1.91, *SD* = 1.14).

Testing Assumptions. Table 3 shows the correlation matrix for the variables of interest. The eight assumptions for multiple regression, according to Laerd Statistics (2018), were tested and met.

Table 3

Correlations Among Centrality Variables and Chat Call-Outs

	Incoming comments	Outgoing comments	# work groups	T1 Eigenvector
Outgoing comments	-.84			
# work groups	.95	-.81		
T1 Eigenvector	-.27	-.15	-.37	
T2 Eigenvector	-.33	.20	-.36	-.01

Notes: *n* = 11

A multiple regression model, using an Enter procedure, demonstrated that Eigenvector at Time 1, Eigenvector at Time 2, and the number of work groups could be used to predict the number of Incoming comments, R = .96, $R^2 = .92$, $F(3, 7) = 26.27$, $p < .001$. Table 4 displays the regression coefficients for predicting Incoming Comments. The examination of these coefficients indicates only the number of work groups makes a significant contribution to predicting the number of incoming comments, t (9) = 7.97, $p < .01$. Furthermore, the number of work groups is positively associated with the number of incoming comments, indicating directors involved in more workgroups received more comments.

Table 4

Regression Coefficients for Predicting Incoming Comments.

	B-weights	Std Error	Beta	t	sig
# work groups	2.46	.31	1.00	7.97	<.01
T1 Eigenvector	1.11	1.01	.13	1.10	.31
T2 Eigenvector	1.55	1.72	.11	.90	.40

A multiple regression model, using an Enter procedure, demonstrated that Eigenvector at Time 1, Eigenvector at Time 2, and the number of work groups could be used to predict the number of Outgoing comments, R = .96, $R^2 = .92$, $F(3, 6) = 23.11$, $p < .001$. Table 5 displays the regression coefficients for predicting Outgoing Comments. The examination of these coefficients indicates both the number of work groups and Eigenvector at Time 1 make significant contributions to predicting the number of outgoing comments. Furthermore, the number of work groups is negatively associated with the number of outgoing comments, indicating Directors involved in fewer workgroups give more comments.

Table 5

Regression Coefficients for Predicting Outgoing Comments.

	B-weights	Std Error	Beta	*t*	sig
# work groups	-1.46	.18	-1.09	-8.03	<.01
T1 Eigenvector	-2.61	.59	-.56	-4.42	<.01
T2 Eigenvector	-1.67	1.07	-.20	-1.56	.17

Chapter 4

Discussion

Summary of Findings

The results showed that, with regard to incoming comments, individuals in two or more workgroups had more incoming comments than those in only one workgroup. These findings supported the first hypothesis and were not surprising, since those in more work groups had more opportunities to strengthen others, adding value to other members in the network. For outgoing comments, contrary to the original hypotheses, results indicated that individuals in fewer work groups were more likely to send outgoing comments, showing appreciation for other network members and complying with the prompt. There are several possible explanations for this unexpected pattern, which may be linked to other unassessed variables such as personality, communication style, or previously established connections outside the network.

Interestingly, individuals in one work group were found to be more central in the formation of the network connections at Time 1 (June 2019). The centrality measured at T1 was likely reflective of pre-existing relational ties outside the network. Members' eigenvector centrality did not differ significantly at T2 as a function of the number of work groups to which they belonged. This shows that the individuals with lower centrality at T1 who signed up for multiple work groups became more similar at T2 to directors who started T1 with higher centrality. In other words, those in more work groups formed more ties because of their workgroup involvement. The lack of significant difference in centrality at T2 indicates greater overall density, suggesting increased collaboration across the network.

Higher connectivity was anticipated among individuals from the same discipline, based on the principle of homophily (e.g., BHC vs other professions, gender, and workplace variables; McPherson et al., 2001) and this hypothesis was not supported. This unexpected finding makes sense when considering the research regarding relational ties being stronger than individual characteristics (Katz et al., 2004). Results of the present study support the idea that there are multi-faceted ways to form or retain relational ties in a network. One way is through workgroups but another significant factor is previous relationships and on-going or previous collaboration outside of the network. For example, of some members who were on boards together elsewhere or had worked closely together in other settings had and strengthened their pre-existing ties. This finding that demographics and discipline had no significant relationship with the variables examined in this study is consistent with the principle that relational ties are more powerful than shared attributes (Marin & Wellman, 2011). These results are a confirmation of the values of the IPC Institute in that the connections in the ICPI network did not occur based on gender, discipline, or affiliation with the university. Creating work groups within an interdisciplinary team addressed barriers related to homophily and relied on the principle that relational ties are stronger than shared attributes. The fact that there was no difference in centrality at T2 suggested that those who entered the network without many relational ties became more connected as a function of work group involvement, whereas those who were more central at the beginning of the network joined fewer work groups and maintained the same level of centrality due to initial relational ties.

Implications

As a board of directors, the IPCI seeks to promote interdisciplinary collaboration through modeling and increasing collaboration among their own board members. The findings in this study have several implications for interdisciplinary network functioning in primary care teams.

One of the takeaways from the present study is that there are multiple factors that influence collaboration. When considering how to increase interdisciplinary collaboration, it is important to consider relationships (personal or professional) among members as well as to create opportunities for subgroups to connect through working together on a shared project. In light of the results, it would helpful to assess pre-existing connections and encourage teams to be involved in more than one work group in order to increase engagement in the network.

Limitations

One significant limitation of the present study is the small number of participants. Despite the many benefits to using SNA with small groups, researchers can easily over-extrapolate from one network to another level without sufficient support (Katz et al., 2004). Although the use of effect sizes standardizes the results across all sample sizes, small samples sizes still result in larger error terms (e.g., confidence intervals and standard deviations). It is possible that there may have been more significant results with a larger sample size. In addition to the small number of participants, the current study collected work meeting comments from one meeting of many throughout the year. The virtual format of the meeting did not allow for ruling out external influences such as environmental interruptions, technical difficulties, or "Zoom fatigue."

Another limitation of the present work is the lack of additional information about the participants, such as career satisfaction, burn-out, and previous experience in interdisciplinary collaboration which could have ruled out many potential confounding variables. This study was limited to quantitative data and lacked qualitative data (e.g., interviews) to explore other aspects of network engagement, such as reasons for choosing work groups, feelings about membership in the network, or additional information about existing ties in the network.

Recommendations for Future Research

Future research with the IPCI board may benefit from exploring pre-existing connections to other members as a potentially important variable to consider. Furthermore, the present study did not assess why some in the network chose more work groups than others. As the network continues to develop and increase in collaboration among various disciplines, future SNAs with additional qualitative data regarding the nature of relational ties, communication ties, and outside factors would be useful.

This research could be expanded and applied to interdisciplinary medical teams using formation of work groups as an intervention to increase network engagement, communication, and collaboration. Several SNA studies have shown the value of increased centrality and outcomes in a hospital setting (Cunningham, 2011). Considering the lack of studies using SNA with primary care teams, future research could utilize SNA with primary care teams and explore centrality in primary care teams related to patient outcomes and efficient interdisciplinary collaboration.

Executive Summary

SNA is a valuable method to analyze the interworking of interdisciplinary networks to support and enhance collaboration among diverse professionals in the health sector. The present study revealed the importance of influence centrality (e.g., eigenvector centrality) and work group involvement in the IPCI network as relates to the value and communication patterns of its members.

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Appendix A

Curriculum Vitae

CONSUELA HEGEMAN

Education

PsyD **Graduate School of Clinical Psychology, George Fox University**

Anticipated graduation, May 2021

Dissertation: "Graduate School Peer Relationships and Early Career Success" Committee: Kathleen Gathercoal, PhD (chair), Mary Peterson, PhD, Elizabeth Hamilton, PhD

MA **Graduate School of Clinical Psychology**

George Fox University, May 2018

BA **Psychology**

George Fox University

Graduated *Cum Laude,* May 2016

Practicum Experience

- **Doctoral Psychology Intern, Summer 2020-Spring 2020**
  Aurora Mental Health Center; Early Child and Family Center
  Responsibilities: Provide therapy with children (ages 0-6) and caregivers in a community mental health center. Activities include relational assessment, dyadic therapy, and maternal mental health support.
- **Pre-Internship Behavioral Health Consultant/Therapist, Fall 2019-Spring 2020**

The Children's Clinic-Newberg
Responsibilities: Provide patient consultation as part of primary care team in a pediatric primary care clinic. Activities include warm hand-offs, brief intervention/follow-up visits, crisis intervention, and a small caseload of long-term therapy patients.
Supervisors: Celeste Jones, PsyD, ABPP, Collin Dean, PsyD

- **Practicum II Behavioral Health Consultant Fall, 2018-Spring 2019**
  Salud Medical Center
  Responsibilities: Provide consultation for patients and providers in a primary care setting. Coordinate patient care and provide brief intervention and psychoeducation.
  Supervisor: Juliette Cutts, PsyD, Jessica Beeghly, PhD
- **Practicum I Therapist Fall 2017-Spring 2018**
  George Fox University Behavioral Health Clinic
  Responsibilities: Provide evidence-based therapy. Contact and coordinate therapeutic care for clients.
  Supervisor: Dr. Joel Gregor, PsyD,
- **Pre-Practicum Therapist- January 2017 – May 2017**
  George Fox University
  Supervisor: Dr. Andrews, PhD, MSCP, ABPP
  Responsibilities: Provide psychotherapy for undergraduate students. Developed skills in electronic record keeping and case management.

Other Work Experience

- **Summer Intern 2016**
  Friendsview Retirement Community
  Responsibilities: Worked with residents in memory care and nursing care to provide therapeutic activities.
  Supervisor: Judie Lawrence, Recreational Therapist, jlawrence@friendsview.org

Research Experience

- **Peru Research Trip 2018**
  Traveled to Iquitos, Peru with a group of psychology undergraduate students and helped participate in data collection in research with indigenous tribes. Research explored resiliency, executive functioning, and strengths in youth of tribes in rural villages, and co-lead focus groups with tribal leaders.

Publications/Presentations

Hughes, I., **Hegeman, C.**, Brown, S., Gathercoal, G. (2019). Exploring the Predictive Validity of the Native Self-Actualization Personality Assessment on an Undergraduate Sample. *Presented at Oregon Psychological Annual Conference 2019* in Eugene, OR.

Webster, K., Sallee, C., **Hegeman, C.,** Peters, K., Goodworth, C. (2019). *Enhancing population health with a marginalized group: targeting faculty's intrapersonal approaches*. A poster accepted to be presented at the annual meeting of the Oregon Psychological Association, Eugene, Or.

Professional Affiliations

- American Psychological Association, Student Member, 2016-Present
- Child and Adolescent Student Interest Group, Member, 2016-Present
- Multicultural Student Interest Group, Member, 2016-Present

Volunteer Work

- **Aquaponics Farm Build: Fly Fishing Collaborative-August 2019**
  Iquitos, Peru
  Worked as a team to construct a self-sustaining aquaponics farm at an elementary school in order to provide additional food and income for a safe home for young girls rescued out of sex trafficking. Additionally, the farm is intended to be incorporated as part of the learning curriculum at the school.

- **Volunteer Service Trips: Villa Esperanza- July 2014, August 2015, June 2017**
  Managua, Nicaragua
  Volunteered with a team through Forward Edge International.
  Activities included: relationship building and group activities with at-risk adolescent girls in the home, service activities at local elementary schools (i.e. cleaning, painting), and volunteering as assistants at a school for children with disabilities.

Teaching Experiences

- **Integrative Topics 2 - Teaching Assistant, Fall 2019**
  Fall 2019, George Fox University
  Class Description: Lecture, reading, and discussion regarding topics

related to diverse worldviews and spiritual perspectives. (e.g. definitions of health, god image, embodiment, indigenous health).
Responsibilities: Grade papers, developing writing prompts, coordinating additional class meetings, providing individual feedback, and class communication regarding assignments.

- **"Development of Language and Communication Skills"-Guest Lecturer, October 2019**
  George Fox University, Newberg, OR
  PSYCH 311- Child Development
- **"Emotion and Motivation", Guest Lecturer, Spring 2018**
  PSYCH 150 - General Psychology
  George Fox University

Supervision Experience

- **Student Supervision, Fall 2019**
  George Fox University
  Description: Conducted weekly hour-long supervision and mentorship related to professional development with practicum I student as part of supervision course training.

Relevant Courses

Psychopathology
Ethics for Psychologists
Lifespan Development
Family Therapy
Psychometrics
Social Psychology
Selected Topics: Integrated Primary Care
Theories of Personality and Psychotherapy
Clinical Foundations I, II
Personality Assessment
Integrative Approaches to Psychology and Psychotherapy
Learning, Cognition, and Emotion
Child and Adolescent Assessment

Cognitive-Behavioral Therapy
Cognitive Assessment
Psychodynamic Psychotherapy
Bible Survey for Psychologists
Research Design
Multicultural Psychology
History and Systems of Psychology

Neuropsychological Assessment and Interpretation

Consultation, Education, and Program Development

Statistics

Biological Basis of Behavior

Professional Issues

Supervision and Management

Spiritual and Religious Diversity in Professional Psychology

Christian History and Theology Survey

Child and Adolescent Treatment

Projective Assessment

Spiritual and Religious Issues in Psychology

Professional Trainings

September 2019 Promoting Forgiveness
Everett Worthington Jr., PhD
George Fox University

March 2019 Foundations of Relationships Therapy—The Gottman Model
Douglas Marlow, PhD
George Fox University

February 2019 Opportunities in Forensic Psychology
Diomaris Safi, PsyD and Alex Millkey, PsyD
George Fox University

October 2018 Old Pain in New Brains
Scott Pengelly, Ph.D.
George Fox University

September 2018 Spiritual Formation and the Life of a Psychologist: Looking Closer at Soul-Care
Lisa Graham McMinn, Ph.D., and Mark McMinn, Ph.D.

March 2018 Integration and Ekklesia
Mike Vogel, PsyD
George Fox University

February 2018 The History and Application of Interpersonal Psychotherapy
Carlos Taloyo, Ph.D.
George Fox University

November 2017	Telehealth Jeff Sordahl, PsyD. George Fox University
October 2017	Using Community Based Participatory Research (CBPR) to Promote Mental Health in American Indian/Alaska Native (AI/AN) Children, Youth, and Families Eleanor Gil-Kashiwabara, PsyD. George Fox University
February 2017	Domestic Violence: Victims and Perpetrators Patricia Warford, PsyD., and Sgt. Todd Baltzell George Fox University
February 2017	Native Self-Actualization: Its Assessment and Application in Therapy Sydney Brown, PsyD. George Fox University
November 2016	When Divorce Hits the Family: Helping Parents and Children Navigate, Wendy Bourg, Ph.D. George Fox University
October 2016	Sacredness, Healing, and Naming: Lanterns Along the Way Brooke Kuhnhausen, Ph.D. George Fox University

Additional Education Opportunities

- **Attachment in Psychotherapy Certificate Course, Spring 2018**
  George Fox University
  Description: Seminar training on various topics related to utilizing Emotion Focused Therapy and Attachment Focused skills in individual, group, and family therapy.

Languages

- **English** (First Language)
- **Spanish**
  (Based on ACTFL Proficiency Guidelines)
  Listening: Advanced High to Superior
  Speaking: Intermediate High

Reading: Intermediate High
Writing: Intermediate Middle

- **French**
  (Based on ACTFL Proficiency Guidelines)
  Listening: Advanced High
  Speaking: Advanced High
  Reading: Advanced Low
  Writing: Advanced Low

References

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