

THE DAWN OF ADVANCED COLLABORATIVE PRACTICES:  
CHARTING TRANSDISCIPLINARY SYNERGIES THROUGH  
THEMATIC AND SOCIAL NETWORK ANALYSIS WITHIN  
BOISE STATE'S GRAND CHALLENGES INITIATIVE

by

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A thesis  
submitted in partial fulfillment  
of the requirements for the degree of  
Master of Arts in Anthropology  
Boise State University

Saturday 24<sup>th</sup> February, 2024

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BOISE STATE UNIVERSITY GRADUATE COLLEGE

**DEFENSE COMMITTEE AND FINAL READING APPROVALS**

of the thesis submitted by

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Thesis Title: The dawn of advanced collaborative practices: Charting transdisciplinary synergies through thematic and social network analysis within Boise State's Grand Challenges initiative

Date of Final Oral Examination: 01 March 2024

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## **DEDICATION**

In loving memory of Shane Gaudio, my husband, who was the bedrock of my academic pursuits, and in honor of Sylvia Milner, my mother, whose resilience and support have been my guiding light. Shane, your dedication to my dreams was unparalleled, and Mom, your unwavering support in the face of adversity has been my salvation. Together, you both have shaped my path, and this achievement is as much yours as it is mine.

## **ACKNOWLEDGMENT**

This journey would not have been possible without the unwavering support and guidance of many individuals whose contributions have been invaluable. First and foremost, I extend my deepest gratitude to Dr. John Ziker, my academic advisor. His insightful guidance, trust, and encouragement to forge connections between my thesis and my role as a Graduate Research Assistant (GRA) have been fundamental to my success. Dr. Ziker's approach to mentorship, emphasizing autonomy and responsibility, has not only enhanced my academic work but also allowed me to explore my research interests with creative freedom. His early advice to seek out knowledge and utilize resources provided a strong foundation for my work, for which I am eternally grateful.

I am also deeply thankful to the Social Network Analysis Project (SNAP) team, including Dr. Vicken Hillis, Dr. Stephen Crowley, Dr. Ellen Shafer, Dr. Ellie Dworak, Jana LaRosa, and Michelle Grek. Joining this team as a GRA offered me a pivotal head start, thanks to the groundwork already laid by this group of remarkable researchers. The knowledge shared, the discussions held, and the resources provided by the team were instrumental in shaping my research. The SNAP team's collective wisdom and the initial work they had completed allowed me to dive deep into my thesis with a clear direction and purpose.

Special thanks go to all the individuals who participated in my survey and inter-

views. Their willingness to share their experiences and insights added immeasurable value to my research, enriching my findings and contributing to the depth of my analysis.

I am grateful to the Division of Research and Economic Development (DRED) for their financial support of my position as a GRA. This support was crucial in facilitating my research and academic endeavors.

Lastly, I cannot overlook the companionship and support of my dog, whose insistence on daily walks and adherence to a routine provided me with the much-needed balance between work and well-being. These breaks were not only refreshing but also a reminder of the importance of self-care throughout this intense academic journey.

To all mentioned and those unmentioned who contributed in various ways to my thesis and academic growth, I extend my heartfelt thanks. Your support has been a cornerstone of my achievements.

## ABSTRACT

Social networks structure the flow of information and relationships within and across various social groups at various scales. Within higher education faculty, social networks have been found to influence the adoption of evidence-based instructional practices and interdisciplinary research performance. This study examines social networks in research collaboration at the university to understand how structured support initiatives affect interdisciplinary collaboration and collaborative practices among faculty. **Purpose:** The study has three aims: 1) to characterize existing collaborative research practices under the university systems and policies in effect at the start of this project in a sample of faculty researchers; 2) to gain a better understanding of the historical network structure of research using collaborative grant proposal data; and 3) to understand the network characteristics of recently-established, thematically-focused research teams that the university-sponsored to address "Grand Challenges" — wicked problems as they manifest regionally in Idaho. The thesis, thus, provides two types of baselines for assessing future social networks of research collaboration and collaborative practices: the overall collaborative grant proposal network and the influence of small research team networks. **Hypothesis:** Diverse social networks lead to more innovative thinking, greater productivity, and the overall value of research. Networks that exhibit parochialism and inequality are less innovative and productive and tend to benefit those already successful. Brokers can work for the

benefit of themselves and like individuals or bring along those less involved in the network. **Methods:** I conducted semi-structured interviews of  $n = 5$  faculty at Boise State on research collaboration. Social network analysis methods were utilized to analyze a complete network of collaborative grant proposals at Boise State from 2016 to 2020, including whole network statistics and predictive modeling using exponential-random graph methods (ERGM) to assess predictors of tie formation. A survey of Grand Challenges research team members was implemented to map networks and understand the composition diversity of these teams. **Statistical Analysis:** ERGM results of the grant proposal network indicate the two strongest predictors of tie formation are geometrically weighted predictors of degree — the number of each faculty member's connections in the network — and geometrically weighted edgewise-shared partners — the propensity of friends of friends to develop a connection (triadic closure). These two predictors are confounded: GWD indicates the dispersion of edges (collaborative proposal partnerships), while GWESP indicates the prevalence of triangles, thus the concentration of edges. Additional predictors in the collaborative grant proposal network include two types of homophily — the tendency to make connections among like individuals. The ERGM also considered the total volume of edges in each college. **Results:** Thematic analysis of interviews reveals a complex interplay between academic culture, institutional structures, and interpersonal dynamics shaping collaboration. Analysis of the collaborative grant proposal network shows overall growth of the network from 2016 to 2019 then a significant reduction in the size of the network with an increase in connectedness in 2020, ostensibly due to the COVID pandemic. In 2020, despite the network's adaptation to challenges, such as the COVID-19 pandemic, the distribution of individuals with high between-

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## NOMENCLATURE

- $\sigma$       The mass of one angel
- $\sigma_I$      The number of angels per needle point
- $\sigma_\mu$     The number of angels per unit area
- $\sigma_{1/\lambda}$  The total mass of angels per unit area
- $\sigma_L$      The area of the needle point

# CHAPTER 1:

## INTRODUCTION

### 1.1 Scientific Discovery for Wicked Problems

Can scientific discovery pave the way for solving society's most complex challenges? In an era where complexities intertwine with every aspect of societal progress, understanding and addressing wicked problems becomes a necessity. A "wicked problem," as described by Rittel & Webber (1973), refers to complex social challenges characterized by their intricacy and resistance to straightforward solutions. These problems, such as those outlined in the United Nations' Sustainable Development Goals (SDGs), are marked by their interconnectedness, and the repercussions ripple through various social systems. Social processes within these challenges are likened to networks, where each action creates a web of effects, underscoring the importance of considering the broad, interconnected systems (Rittel & Webber, 1973). These problems necessitate a comprehensive approach that blends scientific inquiry with innovative policymaking.

This thesis explores how research collaboration has been structured at one university and how these structures can be augmented to better address these multifaceted issues. Collaborative research teams, especially those that span different disciplines at academic institutions and include community stakeholders, are recognized to produce the highest impact work and most groundbreaking innovations (e.g., Sonnen-

wald, 2007; Disis & Slattery, 2010; Hart, 2000; Enns *et al.*, 2023; Lieberknecht *et al.*, 2023). Boise State University (Boise State), recognizing the urgency and complexity of local, regional, and national societal issues, is invested in the ambitious Grand Challenges (GCs) initiative. This initiative's multivariate approach, settled as the cornerstone of Boise State's strategic plan, is designed to foster a transdisciplinary culture of research and creative activity. The University's Center of Research and Creative Activity (CRCA) is pivotal in this endeavor, leading the charge by investing in an Interdisciplinary Research Accelerator (IRA) model (LaRosa, 2023a).

Acknowledging the increasing emphasis in management and organizational studies on researching teams addressing grand societal challenges (Bednarek *et al.*, 2023, citing George *et al.*, 2016; Harley & Fleming, 2021, p.133), the CRCA has identified the need for comprehensive research evaluating the impact of their researcher support plan. This observation led to the formation of the Social Network Analysis Project (SNAP), asking, "How do the GCs investments change collaborations across campus?"

This thesis, set against this backdrop, aims to describe the structural and relational dynamics among Boise State faculty and staff, focusing on understanding the state of the collaborative environment before and during the GCs investments. By analyzing these dynamics, this research seeks to understand and elucidate how these investments have altered collaborative patterns across campus. This exploration will not only contribute to understanding the immediate effects of the GCs investments but also serve as a foundation for future studies to track ongoing collaboration changes. Additionally, this study aims to highlight areas requiring targeted interventions, thereby enhancing the efficacy of Boise State's GCs' initiative addressing

Idaho's wicked problems, contributing to the global pursuit of SDGs.

**Thesis Statement:** This thesis posits that through a detailed analysis of the structural and relational dynamics within Boise State University's Grand Challenges initiative, significant insights can be gained into enhancing interdisciplinary collaboration. These insights are crucial for addressing complex societal challenges and contribute to advancing the field of social network analysis in academic settings, thereby informing strategies to optimize collaborative efforts for societal progress.

## 1.2 Advancing Idaho: The Grand Challenges

The inception of Boise State's GCs initiative can be traced back to 2015 when Jana LaRosa, the Assistant Vice President for Research Advancement and Strategy (AVPR) in the Division of Research and Economic Development (DRED), inspired by institutions like the University of Texas Austin (UT Austin), began contemplating Boise State's own GCs (LaRosa, 2023b, personal communication, September 25). UT Austin's Planet Texas 2050 (PT2050), as analyzed by Lieberknecht *et al.* (2023), exemplifies an innovative, collaborative, interdisciplinary ethos. This interdisciplinary ethos supports researchers in crafting their own thematic roadmaps and provides a useful comparative framework for understanding team dynamics within Boise State's GCs.

In 2019, Boise State's Interim Vice President of Research (VPR) Harold Blackman, Interim Provost Tony Roark, and President Marleen Tromp put out a call to campus asking faculty to send in 2–3-page proposals on what could be theme areas for the GCs (LaRosa, 2023b, personal communication, September 25). They looked at the approximately 150 submissions and then put together five different thematic areas (LaRosa, 2023b, personal communication, September 25) with two primary

challenges: “Resource Nexus for Sustainability” and “Healthy Idaho” (Research and Economic Development, 2024). This process demonstrates the faculty’s active role in shaping the GCs, reflecting the relational dynamic and collaborative spirit central to this thesis.

The GCs Resource Nexus for Sustainability and Healthy Idaho addresses global challenges regionally. The Resource Nexus for Sustainability GC embodies SDG goals like access to clean water and sanitation, promoting affordable and clean energy, and fostering sustainable urban and community development (United Nations Department of Economic and Social Affairs, 2024). This initiative integrates various scholarly disciplines and stakeholders, aiming to build resilient urban and rural systems through a collaborative nexus of scholars and practitioners. Similarly, the Healthy Idaho GC is focused on interdisciplinary and community-engaged research that improves physical and social conditions to foster healthy and thriving communities throughout Idaho (LaRosa, 2023b, personal communication, September 25).

Boise State’s strategic plan, “Blueprint for Success 2021-2026,” outlines key goals encompassing educational access, research advancement, and community engagement. The GCs initiative, particularly aimed at advancing research and creative activity, intersects with all these goals, showcasing its multifaceted impact on the university’s vision (Boise State University, 2024). Notably, Goal 3 specifically highlights the GCs initiative as a pivotal strategy for research advancement (Boise State University, 2024). However, the GCs initiative’s influence extends beyond this single goal: it actively contributes to all five goals, embodying the diverse strategies outlined in the blueprint. This thesis will highlight how the GCs initiative enhances research and aligns with Boise State’s broader objectives, contributing significantly to the



**Figure 1.1: The Healthy Idaho GC outlines key areas for collaborative efforts to improve health outcomes across the state. These areas include One Health, emphasizing the human-environment-animal intersection; Environmental and Workplace Health; K-16 Health, focusing on youth wellness and education; Rural Health, addressing equity and access; Community Health, underlining social determinants; and spans Computational, Personalized, Clinical, Lifespan, and Mental/Behavioral Health. Research teams might explore innovative solutions across these dimensions to foster comprehensive well-being and address the multifaceted health challenges in Idaho's diverse communities.**

realization of the university's vision for success. This backdrop of interdisciplinary and collaborative effort within Boise State's strategic framework is pivotal to this thesis, as it underscores how the GCs initiative not only advances research but also supports broader institutional goals.

### 1.3 Understanding Collaboration: SNAP

SNAP is a research team dedicated to understanding faculty collaboration at Boise State in the context of the impact of the GCs initiative. The team includes staff and faculty across campus, including Anthropology, Philosophy, Human-Environment Systems, the School of Public and Population Health, the Library, and DRED. Additionally, the team includes a graduate student: me. As a member of this project, I have access to this innovative learning experience, an example of the GCs initia-

tive performing Boise State’s blueprint goal to improve student success Boise State University (2024).

Several research branches were formed to measure the impact of the GCs initiative’s investments. Phase 1 of SNAP moves to characterize research and creative activity at Boise State before and at the start of the initiatives’ programs. This thesis details three branches of SNAP: VAMPIRE, CUPID, and LOVE.

Vicken And Many Persons Interview Research Enterprise (VAMPIRE) is a cheeky name for describing the qualitative expertise of SNAP research branch lead, Dr. Vicken Hillis. Tasked with conducting and analyzing informal faculty interviews about collaboration, VAMPIRE asks, “In what ways do faculty at Boise State’s conceptualize collaboration beyond traditional metrics such as proposal applications and publications?” and “What diverse forms of collaboration are prevalent among Boise State’s faculty, and how do these collaborations manifest in academic settings?” To help answer these questions, chapter three of this thesis thematically analyzes faculty responses from focus groups and semi-structured interviews. The chapter explores themes of academic culture, institutional structures, and interpersonal dynamics, offering insights into the multifaceted nature of collaboration in a university setting.

Collective Understanding of PI Data (CUPID) is a research branch of SNAP that uses social network analysis (SNA) on grant application data to answer three research questions. CUPID asks, “How have the dynamics of grant networks at Boise State evolved, and what factors have influenced this change?” “To what extent have the Grand Challenges initiatives influenced these evolving grant proposal networks?” and “Is it possible to predict the formation and changes in collaborative ties between Principal Investigators (PIs) and Co-PIs within these networks?” Chapter four of this

thesis contains a report on historical grant networks. Collaborative grant proposal networks between 2016 and 2020 are described using network visualizations, whole network metrics, and exponential random graph models (ERGMs) for a comprehensive analysis.

The fifth chapter of this thesis reports on research teams formed out of the GCs initiative. In this project branch, SNAP replicates the mid-point survey by Love *et al.* (2021) to investigate these characteristics in interdisciplinary scientific teams. Budding off VAMPIRE and deemed the LOVE branch, SNAP asks, “How do intensive research collaborations within the GCs initiative evolve and impact the nature of collaborative relationships over time?” It is anticipated that LOVE will survey the team several times over the course of the GCs investments. The LOVE chapter reports the initial survey results, visualizing and comparing various team networks, which provides a dynamic view of interdisciplinary collaboration within the GCs framework.

Through these diverse yet interconnected branches of SNAP, this thesis aims to paint a comprehensive picture of the dynamics of interdisciplinary collaboration at Boise State. The insights gained are instrumental in understanding how such collaborations can be optimized to tackle the wicked problems of our time, aligning with global efforts like the SDGs. In the next chapter, the exploration of collaboration literature takes place, examining the literature that details the value of collaboration, defines its various forms in academia, and outlines teaming concerns.

## CHAPTER 2:

### LITERATURE REVIEW

#### 2.1 The Power of Collaboration in Science

Collaboration is vital for solving complex scientific problems and furthering various political, economic, and social agendas, including thriving democracy, sustainable development, and cultural integration. Collaboration can extend the scope of research projects and foster innovation by providing additional expertise (Sonnenwald, 2007). Disis & Slattery (2010) argues that multidisciplinary research teams have several advantages over single-discipline teams. These advantages include a more extensive knowledge base, wider networks, and the ability to engage in dynamic, connective thinking (Disis & Slattery, 2010). As a result, multidisciplinary teams are better positioned to generate radical innovations Disis & Slattery (2010). Collaboration also increases scientific reliability and success probability by involving multiple perspectives in verifying results (Sonnenwald, 2007). This concept of increased scientific reliability through collaboration is a key consideration in the SNAP project. By examining the nature and outcomes of collaborative efforts at Boise State, this research aims to highlight the pivotal role of interdisciplinary synergies and pathways in enhancing the success and reliability of research projects under the GCs initiative. Such collaborations are not merely a means to advance research quality but are also integral

to bolstering a scientist's credibility within the scientific community. This approach aligns directly with Boise State's blueprint goal 4: fostering a thriving community, underscoring the university's commitment to investing in the interconnectedness of researchers across disciplines as a foundation for a vibrant academic and scientific ecosystem (Boise State University, 2024).

Having established the crucial role of collaboration in advancing scientific discovery, it is pertinent to define what constitutes scientific collaboration. Scientific collaboration is defined as a behavior among scientists that involves sharing meaning and completing tasks toward a common, overarching goal, taking place within a social context (Sonnenwald, 2007). Hart (2000) underscores the value of collaboration in enhancing the quality of academic work. In their study on collaborative publications by university librarians, Hart found that collaborative efforts often result in higher quality outputs than single-authored works (Hart, 2000). This phenomenon is attributed to the diverse expertise, mentoring, and intellectual benefits brought together through collaborative efforts, indicating that multi-authored works tend to undergo more rigorous quality control (Hart, 2000).

Intradisciplinary collaboration, or unidisciplinary (Okraku *et al.*, 2017) or simply disciplinary, is a form of scientific cooperation where participants from the same field contribute and generate knowledge within their specific domain, as noted by Sonnenwald (2007). Moody (2004) describes research specialties within these collaborations as central clusters of scientists instrumental in generating innovative concepts and ideas. Dalton *et al.* (2021) further define a scientific discipline as a distinct field characterized by unique discourses and practices, akin to a specific language code. This "language," encompassing methodologies, terminologies, and theoretical frame-

works, remains largely exclusive to the discipline, providing its practitioners with a framework for focused scientific progress (Dalton *et al.*, 2021).

Interdisciplinary collaborations play a crucial role in addressing global challenges by merging diverse expertise and perspectives, thus enabling a more comprehensive understanding of complex issues. While intradisciplinary collaboration significantly generates knowledge within specific domains, the shift towards interdisciplinary collaborations opens up new avenues for addressing more complex societal issues. Jana LaRosa, the Assistant Vice President for the DRED at Boise State, emphasizes the importance of integrating disciplines (LaRosa, 2023b, personal communication, September 25). She notes that while disciplinary work is valuable for its incremental contributions to specific fields, interdisciplinary work is essential for tackling broader, society-driven questions that single disciplines cannot address alone. This perspective aligns with the growing trend among federal agencies to prioritize interdisciplinary research in funding decisions (Huang *et al.*, 2023; Lyall *et al.*, 2013). Leite & Pinho (2017, p. 31) mention that the increasing focus of funding bodies is on fostering various collaborative arrangements, including partnerships among researchers, cross-institutional collaborations, international and regional agreements, input from peers outside the institution, joint authorship endeavors, programs for visiting scholars, and both interagency and international training groups for research. LaRosa highlights that researchers at Boise State must excel in team-based approaches to capitalize on funding opportunities that demand interdisciplinary efforts (2023b, personal communication, September 25). She points out the need for authentic collaboration between STEM and social sciences, moving away from superficial integrations towards genuinely co-created and co-developed research questions that synergize both domains

(2023b, personal communication, September 25). This shift marks a departure from traditional practices where social science elements were often added as afterthoughts to STEM projects; instead, it calls for an equal and integrated partnership from the outset of research initiatives.

## 2.2 Measuring Interdisciplinary Collaboration

Increasing interdisciplinary and transdisciplinary collaborations is a core goal of the GCs investments. Scientific disciplines must work together to solve complex and large-scale societal challenges like Resource Nexus for Sustainability and Healthy Idaho. Collaborative research is often categorized into three distinct yet interconnected types: multi-, inter-, and transdisciplinary (e.g., Dalton *et al.*, 2022; Sonnenwald, 2007; Lieberknecht *et al.*, 2023). Multidisciplinary research involves various disciplines working in parallel, each contributing their perspective without integrating their efforts (Dalton, Wolff, and Bekker 2021). In contrast, interdisciplinary research signifies a deeper level of collaboration where multiple disciplines converge their methodologies and viewpoints to tackle a common problem (Dalton *et al.*, 2021). Transdisciplinary research transcends traditional academic boundaries by converging research design with external entities such as industry, government, and community stakeholders, thus offering a holistic approach to complex societal issues (Dalton *et al.*, 2022). Understanding these diverse forms of collaboration is crucial for the SNAP project, as it seeks to examine how Boise State's GCs initiative navigates and fosters these varying levels of interdisciplinary cooperation.

Delving deeper into the classifications of collaborative research, Bolger (2021) zeros in on the degree of interdisciplinary research by categorizing discipline distances. Through a study of three established research centers, the study surveys

faculty members on their motivations for joining the centers, their perceptions of interdisciplinary research, and the nature of their collaborative activities. Bolger introduces a novel classification based on the “distance” between collaborating disciplines: “within-discipline” collaborations (e.g., between biologists with different specializations), “short distance” within the same super-discipline (e.g., an engineer collaborating with a biologist), and “long distance” across distinct super-disciplines (e.g., an ecologist working with a social scientist) (Bolger, 2021). This final categorization distinguishes collaborations spanning “hard” sciences (natural and applied sciences) and “soft” sciences (social sciences and humanities), offering a more granular understanding of interdisciplinary research dynamics (Bolger, 2021).

Beyond academic boundaries, expanding our understanding to collaborations involving academia, business, and community groups is pivotal for addressing societal challenges. In this realm, participatory action, a collaborative approach between scientists and community members, values community members’ knowledge, experiences, and values, aiming to integrate these into research projects (Sonnenwald, 2007). Its goal is to generate knowledge that leads to effective social action and solves real-life problems, with the effectiveness of the action determined by participants (Sonnenwald, 2007). To demonstrate the effectiveness of participatory action in bridging academic research with real-world application, two exemplary models are summarized: SPECTRUM and PT2050. These initiatives exemplify how collaborative efforts can address societal challenges by integrating diverse perspectives from academia, business, and community groups.

Enns *et al.* (2023) present a comprehensive study on the SPECTRUM project, showcasing a pioneering approach to tackling societal challenges in Canada. Initia-

ated in 2018, the SPECTRUM Partnership addresses the fragmented nature of social services, which often suffer from a lack of coordination and evaluation, leading to sub-optimal outcomes and resource wastage (Enns *et al.*, 2023). This tripartite model, comprising community organizations, government, and academia, transcends traditional hierarchical frameworks, favoring a more egalitarian, knowledge-sharing approach (Enns *et al.*, 2023). By integrating diverse perspectives and expertise, SPECTRUM effectively navigates the intricacies of public policy, social services, and systems (Enns *et al.*, 2023). The partnership emphasizes community-driven research, leveraging existing data to fill knowledge gaps in social programs (Enns *et al.*, 2023). Their findings are transformed into practical policy proposals, aligning with governmental priorities and offering tangible solutions to complex social issues (Enns *et al.*, 2023). This collaborative model not only fosters holistic solutions but also ensures their relevance and effectiveness in addressing the real-world complexities of the problems at hand, demonstrating a viable path for optimizing public policy development in a collaborative, evidence-based manner (Enns *et al.*, 2023).

Lieberknecht *et al.* (2023) present a comprehensive view of the transdisciplinary climate research PT2050, a model that equally values scientific and humanistic disciplines. PT2050's success in integrating diverse epistemologies and methodologies is credited to its focus on disciplinary equity and its inclusion of community partners in co-designing research, thereby avoiding technological solutionism (Lieberknecht *et al.*, 2023). By fostering an environment where different disciplines and community stakeholders can collaborate as equals, PT2050 serves as an example of how GCs can transcend traditional academic silos to address wicked problems.

Transitioning from focusing on successful transdisciplinary projects like SPEC-

TRUM and PT2050, it's important to address the inherent challenges of such collaborations. Merging various academic disciplines and community insights, transdisciplinary work often faces hurdles due to conflicts with entrenched discipline-based conventions, structures, and norms. Because of this, it is generally more difficult to co-create than aggregate research. This reality calls for understanding the intricate dynamics and challenges research teams encounter in interdisciplinary settings.

### 2.3 Teaming Concerns

Interdisciplinary research often demands significant time, is prone to disagreements, necessitates blending different knowledge systems and methods, and calls for adaptability, thorough planning, and mutual trust within the team (Piqueiras *et al.*, 2023). Piqueiras *et al.* conducted a detailed ethnographic study within a larger, federally funded, interdisciplinary scientific team, employing participant observation, semi-structured interviews, and a focus group over six months. They aimed to uncover and mitigate challenges in team science across institutional, cultural, and interpersonal levels. Their findings highlight that by understanding and addressing the three primary barriers of academic culture, institutional structures, and interpersonal dynamics, targeted team-building exercises and specialized training can be effectively employed to mitigate these concerns (Piqueiras *et al.*, 2023). The SNAP project at Boise State, in embracing these insights, aims to explore how such challenges and proposed solutions manifest within the GCs initiative, thereby contributing to a more effective model of interdisciplinary collaboration.

Bednarek *et al.* (2023) research how grand challenge research teams achieve sustained research impact through time across multiple projects. There is an ebb-and-flow of activities and membership, which needs to be managed (Bednarek *et al.*, 2023).

They acknowledge the increasing demands for impactful research on grand societal challenges and identify several barriers, including institutional constraints, knowledge translation difficulties between researchers and practitioners, and the long timescales required for impactful outcomes (Bednarek *et al.*, 2023). These challenges are compounded by the need for sustained engagement with stakeholders and the integration of diverse perspectives within research teams (Bednarek *et al.*, 2023).

### **2.3.1 Crossing Disciplinary Boundaries**

Interdisciplinary research, while crucial for addressing complex societal challenges, faces inherent difficulties due to varying academic cultures, methodologies, and terminologies. Dalton *et al.* (2022) emphasize that effective interdisciplinary collaboration, organized around a central principle like the GCs, is not without its limitations. Researchers often find it difficult to see beyond their disciplinary confines, a hurdle evident in Boise State's GC initiative Healthy Idaho, where early observations by LaRosa indicated struggles among researchers to envision their work within the broader societal framework (LaRosa, 2023b, personal communication, September 25).

Similar issues were reported by Piqueiras *et al.* (2023), which found that team members often reverted to thinking through their disciplinary lens, leading to conflicting ideologies and tensions in knowledge integration. Differences emerged between trusting team members' expertise and trusting them as individuals, highlighting the necessity of actively creating a culture of trust (Piqueiras *et al.*, 2023). Collaborating with various organizations, communities, and governing bodies brings additional trust challenges, such as differing research goals, ethical practices, and resource availability.

Collaboration failures have been blamed on epistemic and ontological incompatibilities, such as interpersonal or political problems and barriers related to language

and terminology between disciplines (Dalton *et al.*, 2021). In a Belgian study, Duysburgh *et al.* (2012) found these types of barriers within multidisciplinary research groups focusing on information and communication technologies. Using ethnographic methods, including surveys, workshops, observations, and interviews, Duysburgh *et al.* explored the integration of diverse academic and community members. They found that the teams struggled to understand how other members would contribute to that larger, common goal, explaining various reasons why. STEM scientists struggle to understand how social scientists can contribute to a project or see their added value (Duysburgh *et al.*, 2012). Additionally, rapid growth in team size led to increased specialization and differentiation among members, which posed a challenge to maintaining coordination and cohesion Duysburgh *et al.* (2012).

Competition between groups fostered further specialization, creating clusters within the teams and distancing the research groups from their university affiliations (Duysburgh *et al.*, 2012). Teams were structured hierarchically with junior, senior, and head levels, alongside supportive roles like secretaries. However, this structure sometimes led to a sense of exclusion among junior researchers, who had limited involvement and access to information (Duysburgh *et al.*, 2012). These factors lead to researchers not understanding the greater research agenda, which means that the result is an aggregation and not a co-creation of creative work.

In addressing interdisciplinary understanding, the perspective of critical realism, as advocated by Dalton *et al.* (2022), offers valuable insights. Critical realism, combining ontological absolutism (external structures) with epistemic relativism (the subjectivity of human understanding), provides a robust framework for understanding the structures and mechanisms in the real world and, by extension, within interdisci-

plinary teams (Dalton *et al.*, 2022). This philosophical approach assists in unraveling the complexities of interdisciplinary interactions and identifying potential sources of conflict or misunderstanding among diverse team members.

Effective communication is vital for coordination, learning, research integration, and mitigating distrust perceptions. Trust, including cognitive (trust in the expertise of others) and affective trust (emotional bond among team members), is fundamental in collaborations (Sonnenwald, 2007). Critical realism may help in building both cognitive trust and affective trust by acknowledging and valuing the contributions of different disciplines. By recognizing and accommodating different epistemological standpoints, critical realism fosters a constructive working environment where differences are not seen as barriers but as enriching elements of a shared objective reality. Critical realism can be instrumental in addressing STEM scientists' skepticism toward social scientists' contributions, as Duysburgh *et al.* reported. Implementing critical realism in practice could involve structured reflection sessions where team members discuss and acknowledge their disciplinary biases and work towards a shared understanding.

Learning, both explicit and tacit, is a critical component of collaborative research, particularly in interdisciplinary settings (Sonnenwald, 2007). However, learning is often challenging and not typically included in research proposals (Sonnenwald, 2007). Duysburgh *et al.* suggest that plenary project meetings, while bridging gaps between specialties, often missed opportunities for effective collaboration. A more frequent and focused meeting approach based on common research interests was recommended (Duysburgh *et al.*, 2012).

Furthermore, critical realism's emphasis on reflexive thinking encourages team

members to be aware of and question their biases and assumptions, leading to more empathetic interactions and stronger affective trust. Critical realism encourages researchers, such as engineers, to appreciate social science's qualitative, context-rich insights, complementing the quantitative, empirically focused approaches typical of STEM fields.

### 2.3.2 Scarcity of Time

In the GCs initiative, efficient time management and realistic goal setting are key strategies to mitigate the challenges of time scarcity identified by Piqueiras *et al.* (2023). Their study found that a constant perception of being behind and urgency affected project management and task division (Piqueiras *et al.*, 2023). Additionally, a consistent issue was the regret and guilt expressed by team members regarding their inability to dedicate sufficient time to the project (Piqueiras *et al.*, 2023). This scarcity of time also affected the follow-through on tasks, depending on each member's availability and capacity (Piqueiras *et al.*, 2023). Unrealistic timelines and conflicting responsibilities strained investigators and trainees (Piqueiras *et al.*, 2023). The research team faced challenges with project management due to a lack of dedicated coordinators and unrealistic funding expectations (Piqueiras *et al.*, 2023). This was exacerbated by funding institutions' requirements for principal investigators to propose ambitious project timelines, often beyond realistic scopes (e.g., a 10-year project within a 5-year timeframe) (Piqueiras *et al.*, 2023).

Duysburgh *et al.* (2012) also recommend strong project management to solve the difficulties inherent in interdisciplinary work (Duysburgh *et al.*, 2012). The lack of a unified software solution led to confusion, and project websites were viewed negatively (Duysburgh *et al.*, 2012). Multiple funding sources, while providing stability, imposed

greater administrative burdens, particularly on senior researchers and administrators (Duysburgh *et al.*, 2012). The GCs investments include assisting researchers in project management to reduce administrative burdens.

### 2.3.3 Institutional Structures

Various institutional structures, including funding agencies, universities, IRBs, and bureaucratic partners, highlight how these structures shape collaborative research (Piqueiras *et al.*, 2023).

Institutional structures affect the attraction to research collaboration. As Okraku *et al.* (2017) emphasize, the predominance of unidisciplinary collaborations in scientific research is often a result of established organizational structures, training processes, and institutional reward systems. Such collaborations enable rapid consensus-building and efficient results production due to shared training and language (Okraku *et al.*, 2017). Nonetheless, this emphasis on unidisciplinary work often leads to its prioritization in tenure and promotion processes, potentially fostering knowledge silos (Okraku *et al.*, 2017). Lyall & Fletcher (2013) suggests that the preference for disciplinary over interdisciplinary research is often shaped by the funding frameworks of research institutions, which establish the guidelines and priorities governing the allocation of resources. Collaborative work can be marginalized or discounted within departments, especially if only one scientist is involved in a specific collaboration (Sonnenwald, 2007), leading to the creation of knowledge silos and impeding the diffusion of knowledge across disciplines (Okraku *et al.*, 2017). The GCs initiative aims to allow individuals to work in an interdisciplinary way that serves their own disciplinary work (LaRosa, 2023b, personal communication, September 25). Understanding these institutional influences is crucial for the CRCA, as it navigates Boise

State's structures to foster effective interdisciplinary collaboration within the GCs initiative.

### **2.3.4 Interpersonal Relationships & Leadership**

Pre-existing collaboration histories among senior team members set implicit expectations for new members, complicating the team dynamics and contributing to feeling overwhelmed (Piqueiras *et al.*, 2023). Sonnenwald (2007) also addresses concerns about unethical conduct, intellectual espionage, and skewed funding toward collaborative research at the expense of single investigators. Duysburgh *et al.* (2012) noted that internal competition reserved team member collaboration efforts, resulting in some researchers and companies only using the initiative as a funding source. The CRCA must be cognizant of existing collaboration histories and their impact on team dynamics to foster a cohesive interdisciplinary research environment.

Networks of scientific collaboration facilitate the spread of knowledge and innovation throughout various disciplines and institutions (Okraku *et al.*, 2017). Disis & Slattery (2010) describe the connective thinking process through which an individual's innovative idea moves through the team. After being fully evaluated, the idea becomes a sum of the team's input (Disis & Slattery, 2010). Moody (2004) cites theorists who argue that an individual's ideas are a function of their position in a social setting, which is deeply structured by interaction patterns. The shape of the idea can be linked to the structure of a network, and in small groups, ideas and their movement depend on the authority structure (Moody, 2004). Leadership, therefore, plays a pivotal role in the success of these teams, with transformational leaders being essential for motivating, moderating, and mentoring diverse groups (Disis & Slattery, 2010).

Interdisciplinary team members face challenges in publication and dissemination, including finding appropriate forums for interdisciplinary results, consensus on authorship, and different disciplinary expectations (Sonnenwald, 2007). LaRosa gives an example from her personal experience assisting research collaboration.

“In some disciplines, writing papers has less value. They disseminate their work through conferences. That is all they need to get a promotion and tenure. The faculty in a different discipline might need to publish to get a promotion and tenure. This leaves one person stuck writing” (LaRosa, 2023b, personal communication, September 25).

Addressing these issues at the onset of collaboration is critical for the success and recognition of research outcomes. Collaborations may face challenges due to varying informal traditions and norms among disciplines, especially regarding intellectual property sharing. For instance, experimental biologists often patent their ideas, while mathematicians are more open (Sonnenwald, 2007). Model agreements provided by funding agencies can streamline the development of a shared understanding of IP and other legal issues (Sonnenwald, 2007).

## 2.4 Evaluating Scientific Collaboration

Team science collaborations are embedded in a dynamic system encompassing social relationships, cultural contexts, and institutional power structures. This web influences and shapes the nature and outcomes of scientific teamwork. It is essential to study this system to ensure the GCs initiative reaches its outcome goals and to tackle Idaho’s Grand Challenges.

Given these considerations, a spectrum of methodologies has been employed to

study collaboration. Sonnenwald (2007) highlights approaches like bibliometrics, interviews, observations, experiments, surveys, simulations, self-reflection, social network analysis, and document analysis. Each method offers unique insights, shedding light on different aspects of collaboration, from quantifiable data to nuanced interpersonal dynamics. Leite & Pinho (2017, p. 6) further delineate the study of research networks into three distinct levels: “macro,” focusing on national and international contexts; “meso,” addressing organizational or institutional level; and “micro,” exploring interactions within specific research groups.

In this thesis, my approach is multifaceted, addressing the power of collaboration, challenges in measuring interdisciplinary collaboration, and concerns related to teaming, as identified in the literature review. Utilizing several methods and analytical levels, I aim to understand collaboration at Boise State comprehensively. I conduct thematic analysis of semi-structured interviews and focus groups of various Boise State research faculty. I leverage SNA to capture meso- and micro-level network structural patterns. I apply SNA to historical grant proposal networks and describe and compare research team networks. In other cases, the analysis is explicitly generative, positing a micro-level behavioral model that produces a population-level network structure, such as clustering disciplines. This work will aid in the customization of the GCs initiative’s research support plan. It will also contribute to the growing literature on team science and specifically research teams addressing society’s grand challenges.

The upcoming chapter will examine the institutional, cultural, and interpersonal factors influencing collaboration at Boise State. This chapter aims to delve deeper into the collaboration dynamics within Boise State using semi-structured interviews

and focus group data. I explore the culture of collaboration.

# CHAPTER 3:

## VAMPIRE

### 3.1 Vicken And Many Persons Interview Research Enterprise

The previous chapter discussed the critical role of collaboration in addressing complex scientific challenges and advancing broader societal goals, such as sustainable development and cultural integration. By bringing together diverse expertise and perspectives, collaboration not only extends the scope of research projects but also enhances innovation, scientific reliability, and the probability of success (Sonnenwald, 2007; Disis & Slattery, 2010). The importance of multidisciplinary teams in fostering dynamic, connective thinking and achieving radical innovations was emphasized, highlighting the necessity of such collaborative efforts for tackling the United Nations' Sustainable Development Goals (SDGs) and other wicked problems (Rittel & Webber, 1973).

The distinction between intradisciplinary and interdisciplinary collaborations was also explored, noting that while the former focuses on generating knowledge within a specific domain, the latter is crucial for addressing broad, complex issues that transcend single disciplines (Sonnenwald, 2007; Dalton *et al.*, 2021). The value of interdisciplinary research has been further underscored by the support from federal

agencies and the strategic emphasis on team-based approaches at Boise State, as discussed by Jana LaRosa (2023b, personal communication, September 25). This chapter continues to explore the mechanisms and impacts of scientific collaboration in greater detail. In phase 1, VAMPIRE asks, “In what ways do faculty at Boise State conceptualize collaboration beyond traditional metrics such as proposal applications and publications?” and “What diverse forms of collaboration are prevalent among Boise State faculty, and how do these collaborations manifest in academic settings?”

## 3.2 Methods

### 3.2.1 Thematic Analysis

“Thematic analysis,” as described by Jonsen & Jehn (2009), serves as the methodological approach for identifying, analyzing, and reporting patterns (themes) within the data. It systematically sorts data into concepts and thematic categories, facilitating a nuanced understanding of the data’s underlying themes. This technique is instrumental in mitigating research biases during data interpretation by enabling the integration of qualitative and quantitative methods (Jonsen & Jehn, 2009). The process begins with coding, a data reduction technique that distills voluminous data into manageable units of analysis. These units, or **concepts**, are essentially single words or phrases that encapsulate key ideas emerging from the data (Jonsen & Jehn, 2009).

Through thematic analysis, concepts are then methodically grouped into categories. These categories, or **themes**, are cognitive classifications that aggregate objects, events, and observations with shared characteristics (Jonsen & Jehn, 2009). They emerge from the analyst’s insights, evolving into meaningful clusters that rep-

resent second-order concepts (Jonsen & Jehn, 2009). This hierarchical organization of data—from concepts to categories—enables researchers to construct a coherent framework or model that captures the essence of their analysis, thereby providing deep insights into the study’s subject matter (Jonsen & Jehn, 2009).

This methodological approach provides deep insights into the subject matter, as exemplified by the use of NVivo software for the streamlined organization and analysis of qualitative data in this study (Lum, 2020). Responses from participants were individually coded into one concept each. Such structured analysis is crucial for dissecting complex phenomena, including the dynamics of interdisciplinary research.

Answering the need for a general understanding of interdisciplinary research and how it can be successfully integrated and sustained in academic centers and universities, Glied *et al.* (2007) employ thematic analysis on extensive notes taken from directors of interdisciplinary research centers focus groups working to characterize successful and challenges factors facing their centers and university are facing (Glied *et al.*, 2007). The primary challenges identified include fiscal sustainability, faculty recruitment and retention, and leadership sustainability (Glied *et al.*, 2007). Fiscal sustainability involves continuous external funding, managing indirect costs, and securing resources such as space and administrative support (Glied *et al.*, 2007). Faculty challenges relate to adapting to interdisciplinary environments, satisfying departmental criteria, varying expectations across disciplines, and providing incentives for involvement (Glied *et al.*, 2007). Leadership sustainability encompasses the administrative burden and maintaining continuity despite leadership changes (Glied *et al.*, 2007).

Piqueiras *et al.* (2023) work to uncover and mitigate challenges in team science

by employing participant observation, semi-structured interviews, and a focus group method, studying an interdisciplinary team for over six months. They argue that thematic analysis and ethnography can effectively identify and address practical tensions and contextual factors that hinder scientific collaboration (Piqueiras *et al.*, 2023). After intensive data collection, the authors used code from their literature review and compared the findings across the data sources for validation (Piqueiras *et al.*, 2023). The study's central thematic areas include academic culture, institutional structures, and interpersonal dynamics with disciplinary boundaries, scarcity of time, and trust and accountability nested concepts in each theme (Piqueiras *et al.*, 2023).

This thesis aims to enhance the understanding of collaboration at Boise State at the onset of the GCs initiative by outlining the pre-investment status of collaboration and identifying obstacles within the Boise State research culture to collaborative science. The Vicken And Many Persons Interview Research Enterprise (VAMPIRE), a specialized branch of SNAP, is designated to carry out and scrutinize informal interviews with Boise State faculty on collaboration. It seeks to uncover how faculty members define collaboration, moving beyond traditional indicators like proposal applications and publications and exploring additional modes of faculty collaboration. The study categorizes faculty responses into themes through thematic analysis by employing focus groups and semi-structured interviews. This approach is intended to establish a baseline for future longitudinal studies, scrutinizing Boise State faculty's prevailing attitudes and practices concerning collaborative creative endeavors.

The study employs thematic analysis to probe the structural and cultural facets of the Boise State research community. This methodology of integrating focus groups and semi-structured interviews aims to build a comprehensive, multifaceted dataset,

thereby enriching the analysis of faculty collaboration dynamics at Boise State. By amalgamating Social Network Analysis (SNA) and thematic analysis, the research visualizes collaboration trends and identifies meaningful research teams, marrying quantitative network descriptions with qualitative contextual insights.

### 3.2.2 Data Collection

In 2020, the initial data collection phase commenced with faculty focus groups. These groups, formed through self-selection via a “Funding Blast” emailer, were tasked with discussing research communication and the inherent challenges of collaborative endeavors (LaRosa, 2023b, personal communication, September 25).

#### Focus Groups

Facilitators Jana LaRosa and Nancy Glenn led these discussions, recording notes of participant responses. NVivo, (Lum, 2020), grouped the notes into twenty-five concepts ranging from the identity of collaborators (“faculty”, “students”, “relationships”) to the modalities and motivations of collaboration (“skills,” “opportunities,” “funding,” “professional development”), the frequency of interaction (“team communication”), and the logistical and interpersonal challenges encountered (“Connecting with Others,” “Envisioning Collaboration Opportunities,” “Funding,” and “Time”). These were manually classified into nine themes determined by semi-structured interview coding. Figure 3.1 is the focus group hierarchy chart showing codes and sizes of the boxes by the number of coding references. The themes were then aligned with the three primary themes derived from Piqueiras *et al.* (2023): Academic Culture, Institutional Structures, and Interpersonal Dynamics, thus offering a refined lens through which to view the faculty’s collaborative experiences. This alignment

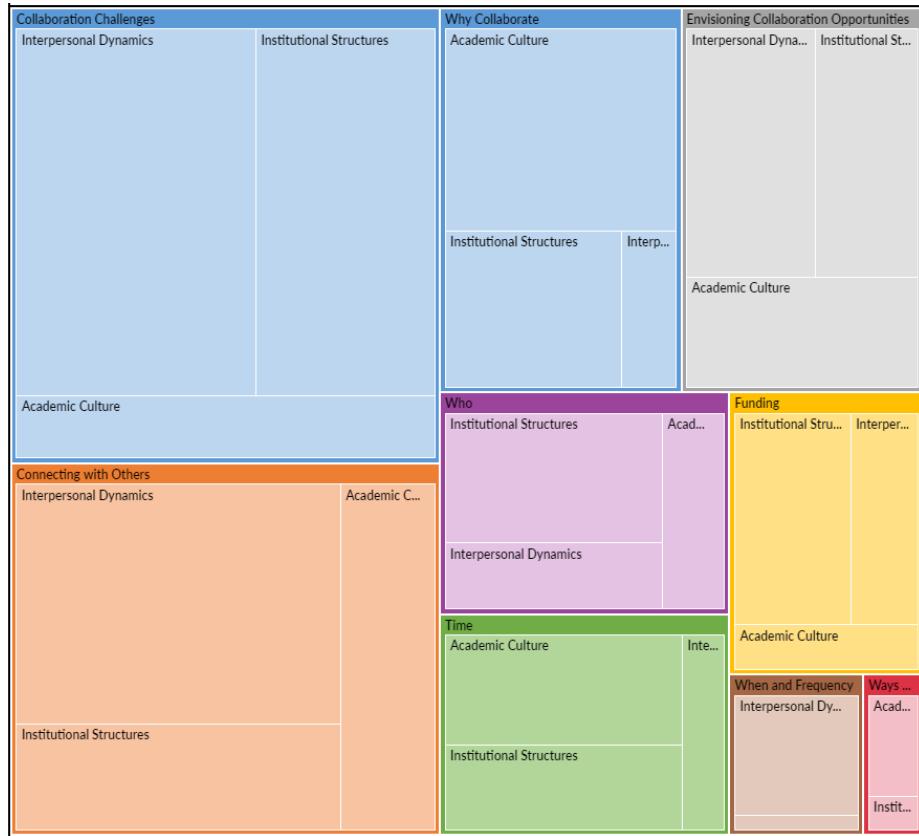
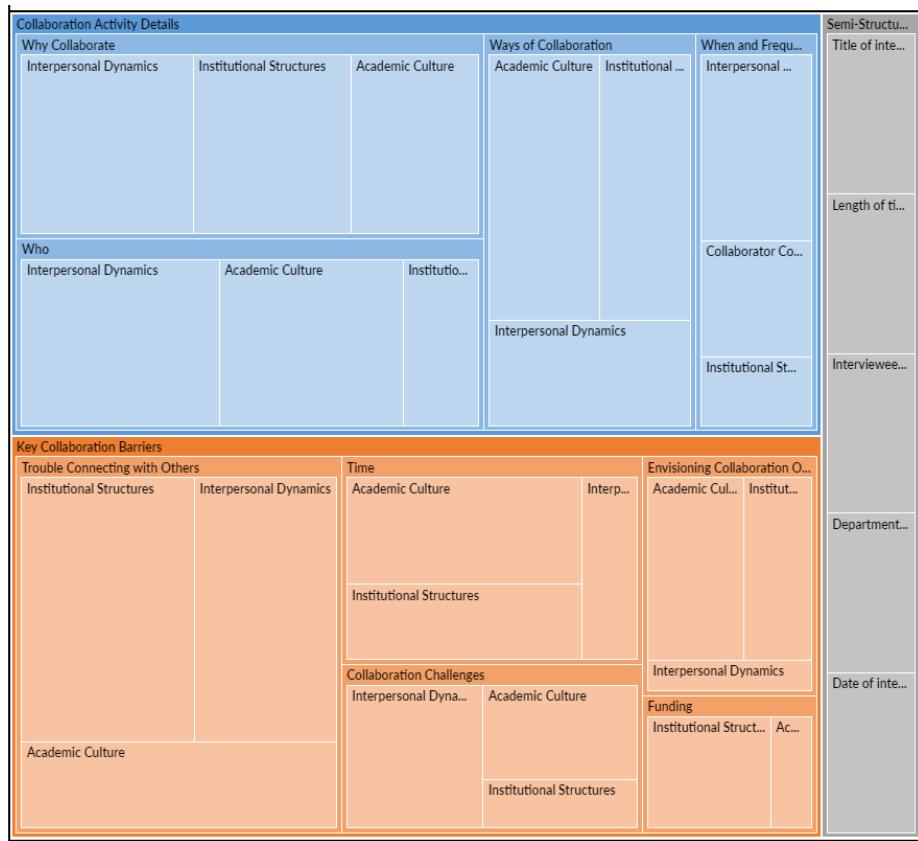


Figure 3.1: The focus group hierarchy chart showing a code comparison by the number of coding references. The outer nine concepts, represented by various colors, were created through the NVivo auto-coding feature. Each concept contains the three primary thematic areas, as identified by Piqueiras *et al.* (2023). The size of the squares represents the proportion of responses encoded under the specific theme.

allows for combining the analysis with the emerging themes from the semi-structured interviews.

### Semi-Structured Interview

Semi-structured interviews were conducted via Zoom between November 2022 and January 2023. The SNAP team meticulously developed the interview script, which spanned various collaborative aspects, from subjective feelings of closeness to collaborators to structural barriers and enablers. Five interviewees were selected from



**Figure 3.2:** The semi-structured interviews hierarchy chart comparing the codes by the number of coding references. The mid-level nine concepts, represented by mid-color intensity, were *generally* created through the NVivo auto-coding feature. Piqueiras *et al.*'s three primary thematic areas are inside most concepts.

the Biology, Psychology, and Anthropology departments due to the convenience of acquaintanceship.

These interviews were transcribed and manually analyzed using NVivo (Lum, 2020). Nvivo's auto-coding feature created many initial concepts, which were consolidated manually by 'likeness' into nine thematic areas, which were subsequently manually organized into two predominant themes: "Collaboration Activity Details" and "Key Collaboration Barriers." A third category, delineated in grey in the figure, contains concepts related to participant demographics and survey specifics, which

were not considered in the analysis. The nine thematic areas were further categorized under three primary themes as identified by Piqueiras *et al.* (2023): Academic Culture, Institutional Structures, and Interpersonal Dynamics.

Figure 3.2 presents a hierarchical chart of the codes derived from the semi-structured interviews, illustrating a comparison of codes by the number of coding references. This structuring facilitates a cohesive and comprehensive analysis, harmonizing the insights gained from both the semi-structured interviews and the broader research context.

## 3.3 Analysis

### 3.3.1 Academic Culture

Academic culture, with its complex web of entrenched norms and subtle resistance to change, plays a critical role in shaping the landscape of collaborative research (Piqueiras *et al.*, 2023). Within this culture, various dimensions emerge, reflecting the multifaceted nature of academic work and the challenges it presents. From the recognition of collaborative achievements and the dynamics of faculty support to the pursuit of novel approaches and the omnipresent pressure of time constraints, academic culture is a tapestry of interactions, expectations, and practices. This section delves into these aspects, untangling how academic culture influences, constrains, and catalyzes the collaborative spirit in research endeavors.

### Achievements and Acknowledgements

The concept of collaboration in academia, particularly through co-authorship on manuscripts or joint principal investigator roles on grants, is a significant marker

of completed creative work and is deeply entrenched in academic culture. This is exemplified in the observation, “To me, it means to be a co-author on a manuscript or a Co-PI in a grant,” highlighting the formal recognition of shared effort and responsibility in research endeavors. However, a nuanced challenge emerges within this context: the potential overshadowing of collaborative efforts by individual achievements. Faculty narratives, such as “not once did anything ever come from that in terms of publication” and “the outcome is not always as beneficial as we hope,” reveal a cultural tension where the value of collaborative endeavors may be undermined if they do not culminate in conventional academic outputs like publications. This tendency to prioritize individual accomplishments over collective efforts poses a critical challenge to collaborative research ethos.

The vulnerability of junior faculty in collaborative projects is particularly noteworthy. They are often more open to engaging in collaborative projects driven by energy and the need to develop diverse research portfolios. However, they face heightened risks, as the sentiment illustrates, “contracts don’t reflect a jr. faculty doing robust research.” This statement underscores institutional barriers that can hinder effective collaboration, pointing to a gap in the support structures for early-career researchers. Such barriers impede collaboration and affect the career trajectory and development of junior faculty. In contrast, senior faculty and more experienced researchers are pivotal in shaping the collaborative landscape. As Allison Simler-Williamson’s experiences suggest, mentorship from seasoned academics provides invaluable guidance and support to less experienced colleagues, fostering an environment of professional growth and development. This mentorship is a cornerstone of academic culture, facilitating knowledge transfer and nurturing research skills among emerging scholars.

### Faculty Support and Departmental Dynamics

The role of departmental leadership and culture in fostering or impeding collaboration emerges as a central theme in academic settings. Faculty anecdotes reveal how shifts in departmental chairmanship can significantly alter the research environment. For instance, one faculty member noted the profound impact of leadership changes on the culture of support and encouragement for research, highlighting the pivotal role of departmental heads in cultivating a conducive atmosphere for collaboration. This underscores the intricate balance between maintaining individual research autonomy and embracing collaborative efforts. Statements like “In the department of psychological science, research, and creative activity are largely autonomous” contrast starkly with reflections on the value of collaborative work, displaying a prevalent culture of individual research efforts in some academic settings.

This theme resonates deeply when considering opportunities for collaboration, particularly in departments where solo endeavors are the norm. It points to the necessity of balancing individual research autonomy with collaborative initiatives. The significance of institutional support in facilitating collaboration is underscored by remarks such as “The department has been supportive with all collaboration” and “They are vital in helping me create space to meet deadlines.” Such comments illustrate how variations in leadership and departmental culture can profoundly influence the extent and effectiveness of collaborative efforts among faculty. Departmental policies and practices, as outlined by Okraku *et al.* (2017), play a formative role in shaping the scientific community’s landscape, encompassing aspects like federal programs, funding opportunities, hiring practices, resource allocation, and graduate training.

Interpersonal dynamics within collaborations also reveal interesting patterns. As

noted by all interviewees, faculty engage in collaborations not only within their departments but also with external professionals and community partners. These relationships, characterized by mutual respect and shared research interests, vary in closeness and formality. However, challenges arise in interdisciplinary collaborations, particularly in communication across different disciplines. Faculty express concerns about the “Lack of exposure to other disciplines” and the difficulties posed by “No shared language.” These issues highlight the necessity for effective communication strategies, such as the ability to “code switch in these environments” and “write for your audience” to bridge disciplinary divides. The need for adaptable communication styles is thus emphasized as a crucial component for successful collaborative work, as it facilitates the integration of diverse perspectives and the smooth flow of ideas.

### **Embracing Novel Approaches**

The process of venturing into new intellectual territories and the challenges of finding common ground across disciplines is a recurring theme in the pursuit of collaboration opportunities. Faculty members describe this journey with statements like, “You are always moving into new intellectual areas gradually,” capturing the essence of academic exploration and the gradual shift toward interdisciplinary work. However, this endeavor is not without its challenges, as indicated by the observation, “I do not see many opportunities where the overlap exists.” Such comments reflect a keen awareness of the difficulties in identifying and developing interdisciplinary collaborations, highlighting a need for more structured opportunities to foster these connections.

Beyond the box of traditional research, the integration of research with teaching and public engagement emerges as a significant collaborative avenue. Faculty

members advocate for a broader conception of academic productivity, as evidenced by sentiments like “Don’t treat research as a single theme - integrate more with teaching” and “Broaden what we think of as research, plus public outreach and engagement.” These perspectives underscore the potential for collaborative efforts that extend beyond conventional research boundaries, encompassing teaching and community involvement. This approach is not merely a suggestion but a call to action, challenging the status quo of academic work.

Integrating teaching, research, and service activities is further illuminated by references such as “Collaborate with our classes and artwork” and “Integration of teaching and service is important.” These insights reveal a holistic perspective on faculty roles, where the silos of teaching, research, and service are not only interconnected but also mutually reinforcing. This integrative approach is essential in cultivating a more comprehensive and multi-dimensional academic culture that values and promotes a wide range of scholarly activities. It speaks to a dynamic understanding of academia, where the traditional boundaries of research, teaching, and service are reimaged to create a more fluid and interconnected scholarly practice.

### **Limited Time**

In academic culture, the perception of time and its constraints plays a pivotal role in shaping faculty experiences and priorities. This is vividly reflected in numerous observations from faculty, such as “Time is the biggest challenge” and “Don’t have enough workload to focus on research.” These comments underscore a pervasive sentiment of time scarcity, which goes beyond mere institutional structures to the very heart of academic culture. It points to an ingrained belief within the academic

community that there is always a deficit of time, fueling a sense of constant urgency. This cultural perspective on time highlights the ongoing struggle of faculty members to juggle their diverse roles in teaching, research, and administrative duties. Rather than being solely a product of institutional demands, this tension is deeply embedded in the academic mindset, shaping how faculty perceive and manage their time.

### **Conclusion**

In summary, academic culture is a potent force that shapes the contours of collaborative research in profound ways. It is manifested in the quest for achievements and acknowledgments, where the balance between individual and collective successes is delicately negotiated. Faculty support and departmental dynamics further color this landscape, illustrating how leadership styles and departmental ethos can significantly impact collaborative endeavors. Embracing novel research, teaching, and public engagement approaches reflects a growing trend toward interdisciplinary and integrative practices, challenging the traditional confines of academic roles. Meanwhile, the pervasive issue of limited time underlines a cultural norm of constant urgency and the struggle to juggle diverse academic responsibilities.

The next section, “Institutional Structures,” highlights that these cultural themes are inextricably linked to the broader institutional context. This section explores how the structures and policies at Boise State further influence and shape the practice of collaborative research.

#### **3.3.2 Institutional Structures**

This section explores the multifaceted role that institutional structures play in facilitating or hindering the collaborative process within academic settings. It delves into

the crucial aspects of resources, infrastructures, and policies that shape the terrain of academic collaboration. Emphasis is placed on the pivotal role of administrators, as highlighted by Allison Simler-Williamson, in providing essential support and navigating the complex bureaucracy inherent in academic departments. The examination includes the infrastructure support necessary for fostering a collaborative environment, the intricate balance of workload policies influencing faculty's ability to engage in research, the nuanced mechanisms of funding structures driving collaborative initiatives, and the vital role of integrating students into the collaborative framework. Each of these components reveals a different facet of how institutional constructs can either support or constrain the collaborative efforts of faculty and students in academia.

### **Infrastructure Support**

Faculty voices echo the sentiment that institutions must develop a deeper understanding and robust support for interdisciplinary research. Phrases such as “University needs to understand what it means for faculty to do interdisciplinary research” and “Make sure the university supports interdisciplinary work” underline the necessity for institutional awareness and explicit support. This perspective points to a gap in current institutional structures – a gap that, if bridged, could significantly enhance the efficacy and productivity of collaborative research endeavors. The emphasis on interdisciplinary work also reveals a broader institutional challenge: adapting and evolving to accommodate and nurture diverse research methodologies and partnerships.

The necessity for physical and strategic infrastructures that promote collaborative research is repeatedly emphasized in faculty discussions. Statements like “creating

opportunity and space for the human connection” and calls for a “central repository for seminars” highlight a significant institutional need. These references underscore the critical importance of designing physical and virtual spaces that encourage interaction, idea exchange, and the nurturing of collaborative relationships among faculty members. Such infrastructures are more than mere conveniences; they are essential frameworks supporting collaborative work’s complex dynamics.

An additional layer of complexity emerges when considering faculty responsibilities and integrating new initiatives. Comments like “It feels like an extra layer of work to do on top of my work” reflect the tension between existing duties and additional collaborative projects. This sentiment illustrates faculty’s ongoing struggle to balance their workload, often exacerbated by institutional expectations. Moreover, the discussion on the need for tenure and promotion policy changes to honor diverse skills demonstrates the structural barriers to interdisciplinary research. These policies often dictate faculty priorities and can inadvertently hinder the pursuit of innovative, collaborative projects.

Incentives, both monetary and in terms of recognition, are cited as crucial motivators for collaborative efforts. Faculty reference the importance of tangible rewards, such as being included in grants or receiving time allocations, to justify their engagement in collaborative projects. These incentives are essential elements that validate and encourage the investment of time and effort in collaborative work. They also serve as recognition of the value and impact of such efforts within the academic community.

## Workload Policy

The intersection of faculty workload policies and research collaboration forms a complex and often challenging aspect of institutional structures. Faculty narratives, laden with references like “Conflicted with existing workload policy” and “No way to reimagine the contract - workload,” lay bare the direct impact of university workload guidelines on the allocation of time for research and collaborative efforts. These policies, deeply embedded within institutional frameworks, often dictate the distribution of faculty time, significantly influencing their capacity to engage in research activities.

The conundrum of effectively managing and prioritizing time amidst diverse responsibilities is palpably felt in the academic community. Statements such as “figuring out what fits, and it adds one more thing to the plate” and the evocative “Hard rule of 3:3 in the COED – teaching is getting cranked up!” reflect the intricate juggling act faculty must perform. The “3:3” rule, a stringent requirement of teaching three classes per semester, epitomizes the substantial teaching responsibilities that can overshadow research endeavors. This scenario underscores a key challenge: balancing the demanding roles of teaching, administration, and research.

The impact of workload allocation on faculty’s ability to immerse themselves in innovative research and collaboration cannot be overstated. Phrases such as “We don’t account for the time to do team science” and “Need free time to be innovative and work through a problem” highlight an institutional blind spot regarding the time necessary for collaborative and creative research pursuits. These statements call for a reevaluation of workload policies to accommodate the time-intensive nature of collaborative research. The essential question is whether institutions can adapt their workload structures to foster an environment where research and collaboration are

not just encouraged but practically feasible.

The narrative also brings to light the need for structural support mechanisms to facilitate dedicated research time. Suggestions like “Could there be mini-sabbaticals to create time for faculty?” and “Clear guidelines about time off and course buyouts that apply across campus” propose innovative solutions to the time dilemma. These ideas signify the need for institutional initiatives such as sabbaticals or course buy-outs, which can provide faculty with the much-needed respite to focus on research. Such measures are not merely conveniences but essential components of a supportive academic environment that recognizes and values the importance of research and collaboration.

### Funding Structures

In the landscape of academic research, funding mechanisms like the “Cobrea grant” and the “One-Health initiative” serve as key drivers for interdisciplinary collaboration. These initiatives, often requiring collaborative efforts across various disciplines, illustrate how funding structures can catalyze interdisciplinary research. However, securing funding in such contexts is fraught with challenges, as encapsulated in the struggle of “Finding funding and collaborators who get it” within “small and interdisciplinary spaces.” This predicament underscores a critical gap in traditional funding models, which may not adequately accommodate the nuanced needs of interdisciplinary projects. The struggle to find appropriate funding sources and collaborators who appreciate the interdisciplinary nature of the work highlights an urgent need for more adaptable and inclusive funding mechanisms that can embrace the complexity of interdisciplinary research.

The control exerted by university administrators over funding resources is a pivotal theme. Statements like “The administrators also hold the purse” and “They hold the keys to that kind of thing” underscore the significant influence of administrative policies and decisions on research funding. This theme highlights the often underappreciated role of administrative structures in shaping the research agenda, directing the flow of funds, and influencing the course of academic inquiry.

Seed grants emerge as a vital component in the funding landscape, serving as crucial initial support for collaborative and experimental research projects. References to “Scaling opportunities to collaborate - seed grants” underscore the role of these grants in laying the groundwork for more extensive research endeavors. Such funding opportunities are essential, especially for interdisciplinary projects that might not fit neatly into established funding categories. The need for financial structures that support experimental and interdisciplinary research is further echoed in statements like “How to fund faculty research that is mindful of engaging students in the classroom and have cross-disciplinary conversations.” These remarks reflect a call for more flexible funding models that can nurture innovative research approaches. The repeated emphasis on the importance of seed grants and funding for pilot studies, as seen in “Under resources - need small pots of money to make space for thought” and “Investment in pilot studies - to develop a track record,” highlights the critical role of initial, modest financial support in catalyzing larger, more comprehensive research projects.

## Student Collaborators

An essential yet complex facet of academic collaboration is the active involvement of students, particularly undergraduates, in research projects. This dimension of collaboration, as exemplified by the experiences of Cindy McCrea and Matthew Genuchi, underscores the pivotal role of mentorship in enriching students' educational journey. These collaborations offer students invaluable hands-on experience in research, contributing significantly to their learning and professional development.

The mentorship of undergraduates in research projects extends beyond conventional teaching paradigms, offering a dynamic and immersive learning experience. Such mentor-student collaborations serve a dual purpose: they provide students with critical research skills and exposure while simultaneously enriching the research capacity and innovation within the academic community. This interaction is a testament to the symbiotic relationship between teaching and research in academia, where each enriches the other.

Despite the apparent benefits, incorporating students into research collaborations is not without its challenges. Statements like "I want to recruit students for a longer period like graduate students." and references to "graduate student access/barriers/silos" underscore the structural difficulties faced in this endeavor. Training and supervising student researchers often requires significant time and resources, and retaining these students through the completion of projects can be a formidable task. These challenges highlight a broader institutional issue: the need for more streamlined and supportive mechanisms to facilitate the involvement of students in research.

The barriers to effective student integration in research often manifest as depart-

mental silos, restrictive academic policies, and limited resources. These structural obstacles can impede the fluid movement and collaboration of faculty and students across various disciplines. Overcoming these barriers requires a concerted effort to create more flexible and accommodating institutional structures. This includes rethinking departmental boundaries, revising policies to facilitate cross-disciplinary student engagement, and allocating resources to support student involvement in research.

## Conclusion

In conclusion, “Institutional Structures” reveals a landscape where collaboration is deeply intertwined with the frameworks and policies of academic institutions. The narratives from faculty members underscore the need for supportive infrastructures that encourage interdisciplinary work, flexible workload policies that accommodate research endeavors, funding mechanisms that cater to diverse and innovative projects, and the seamless integration of students into research collaborations. These structural elements are not just facilitative backdrops but active players in shaping the success and dynamics of collaborative research. The insights gained set the stage for the next focus: “Interpersonal Dynamics.” This final primary theme will delve into the human element of collaboration, exploring how personal relationships, communication styles, and individual motivations influence and are influenced by the collaborative process. As the discussion transitions to this theme, the understanding that academic culture and institutional structures provide the frame upon which interpersonal interactions in academic collaboration are experienced is carried forward.

### **3.3.3 Interpersonal Dynamics**

Grounded in the experiences and insights of faculty members like Allison Simler-Williamson, Cindy McCrea, and Juliette Tinker, this analysis delves into the nuances of trust, respect, role clarity, mutual interests, and the balancing act of managing time demands. These dynamics paint a vivid picture of the interpersonal landscape in academic collaborations, highlighting the importance of understanding and navigating these relationships skillfully. From the initial stages of forming a collaboration based on shared interests and respect to the ongoing management of roles and expectations, these dynamics shape the course and outcome of academic partnerships. The diversity of communication styles, the evolution of relationships over time, and the challenges of aligning individual and collective goals are all integral to understanding the interpersonal fabric of academic collaboration.

#### **Trust and Respect**

Trust and mutual respect shape collaborative relationships within academia. The process of selecting collaborators is often deliberate and strategic, guided by shared research interests and a recognition of excellence in specific areas. This is reflected in the experiences of Cindy McCrea and Shelly Volsche, who underscore the importance of aligning with colleagues and students who possess exceptional skills or knowledge that complement their research endeavors. This selective approach aims to forge productive and synergistic teams, emphasizing the significance of intellectual compatibility and expertise in the collaborative process.

However, establishing and maintaining trust and reliability in these relationships are not without challenges. Statements such as “you have to trust that the person is

going to do what they say they are going to do” highlight the inherent uncertainty and risk in collaborative ventures. The ability to rely on a collaborator’s commitment and follow-through becomes a critical factor in determining the success and viability of joint projects. Concerns about integrating collaboration within one’s research program further compound these challenges, pointing to the delicate balance of trust needed to navigate these partnerships.

The emphasis on trust is complemented by the necessity of collegiality and respect in successful collaborations. The sentiment “If they have the right expertise but are awful as a person, then I won’t try to collaborate with them” encapsulates the importance of respectful and professional interpersonal interactions. This underscores that expertise alone is insufficient; the quality of interpersonal dynamics plays a crucial role in the sustainability of collaborations.

Collaborative relationships, as they unfold over time, often exhibit a dynamic evolution. Allison Simler-Williamson’s description of her collaborative journey, transitioning from mentorship to more balanced partnerships, exemplifies the fluid nature of these relationships. This evolution is reflective of the developmental trajectory in academic careers, where roles and contributions adapt as projects progress and individuals gain experience and insight.

The essence of collaboration in academia is also characterized by a blend of professional courtesy and reciprocal benefit. Juliette Tinker’s interactions with collaborators like Mark McGuire and Rich Beard illustrate a dynamic where professional respect is intertwined with mutual benefit. These relationships are anchored in shared interests and expertise, often culminating in co-authorship on papers and joint grant applications. The notion of reciprocity is central to these dynamics, as evidenced in

the exchange of resources, expertise, and recognition, enriching the collaborative experience. Tinker's collaboration with the University of Idaho's dairy farm is a prime example, where access to specialized resources and expertise was pivotal. Such inter-institutional collaborations underscore the necessity of diverse skills and resources for advancing research, emphasizing the collective strength derived from varied expertise. Interpersonal dynamics in academic collaborations are not limited to active research roles but also encompass supportive functions. Tinker's reference to Denny Stevens, primarily involved in providing letters of support, illuminates a collaborative role centered around professional endorsement rather than direct research engagement. These supportive roles are integral to the academic ecosystem, where peer validation can significantly influence the trajectory of research initiatives and grant applications.

### **Role Clarity, Expectations, and Autonomy**

The interplay of role clarity, expectations, and autonomy emerges as a pivotal theme in interpersonal dynamics. The diversity in modes and frequency of communication among collaborators is a key aspect of academic collaborations. The experiences of Tinker and Genuchi illustrate a spectrum of communication styles, ranging from frequent emails and phone calls to more sporadic face-to-face interactions at conferences. Such variations reflect the flexibility inherent in academic partnerships, where communication strategies are often tailored to suit the project's needs and the geographical distances between collaborators. This flexibility in communication is crucial in maintaining the fluidity and continuity of collaborative work, allowing for timely exchanges of ideas and feedback despite physical separations.

Academic collaborations manifest in formal and informal arrangements, each with

distinct dynamics and implications. As seen in mentor-mentee relationships exemplified by Cindy McCrea, formal collaborations are characterized by well-defined roles and responsibilities. These structured interactions are essential for clarity and efficiency, particularly in guiding and nurturing the development of students in research settings. On the other hand, informal collaborations, such as the collegial interactions described by Allison Simler-Williamson, involve less structured engagements like tracking each other's work and exchanging feedback. These informal exchanges, while less regimented, play a vital role in creating a supportive and intellectually stimulating environment. Formal and informal collaborations contribute significantly to the richness and diversity of academic research culture, offering varying degrees of structure and flexibility.

A recurring challenge in academic collaborations is balancing individual autonomy with collective efforts. This balance is often fraught with complexities, as illustrated in references discussing work distribution and setting expectations. The delicate interplay between maintaining independence in research pursuits and engaging in cooperative efforts is a nuanced aspect of academic collaborations. Conflicts may arise from unclear roles and expectations, potentially leading to inefficiencies and strained relationships. To navigate this landscape, collaborators must establish clear communication channels, agree upon roles, and set realistic expectations from the outset.

The essence of collaboration in academia often lies in the joint execution of research activities. Statements like “developing research protocols, collecting data, analyzing data, and writing that up” and “participating in all components of the research process” highlight the collaborative nature of the research journey. In these

shared endeavors, individuals bring their unique expertise and perspectives, collaborating across various project stages – from conceptualization to dissemination. This theme is integral to academic culture, underscoring the collective effort and interdisciplinary approach that characterize much of academic research. The involvement of diverse talents and skills in these activities enriches the research output and fosters a sense of shared purpose and achievement among collaborators.

### **Mutual Interests**

The genesis of many academic collaborations often lies in the convergence of shared research interests and goals. Juliette Tinker's collaboration with Mark McGuire is a case in point, where mutual interests in dairy research and the availability of unique resources at the University of Idaho served as the foundation for their partnership. These shared interests go beyond mere professional convenience; they are pivotal in advancing specialized research areas, especially where specific expertise or resources are scarce. Such collaborations not only fulfill immediate research needs but also contribute significantly to the broader field of study by pooling together specialized skills and resources. Cindy McCrea points out the benefit of researching with a peer versus a student:

“You have somebody to bounce ideas off of. You know, ‘Which direction should we go with this, and what are the pros and cons.’ You can do that with a student researcher, but often they are just a sounding board. They don’t have the experience to weigh heavily on those discussions” (McCrea, 2023, personal communication, December 15).

The selection of collaborators often hinges on the unique skills and expertise they

bring to the table, complementing those of the lead researcher. The focus group discussions highlight the strategic composition of research teams, emphasizing the value of diverse skill sets. Statements about the need for individuals with methodological knowledge or different skills illustrate the importance of creating multidisciplinary teams. As Allison Simler-Williamson notes, such collaborations are often “greater than the sum of the parts,” signifying the enhanced value derived from integrating varied perspectives and knowledge bases. This diversity not only broadens the scope of research possibilities but also deepens the intellectual richness of the project, enabling a more comprehensive exploration of research questions.

### **Time Demands**

The inherent nature of collaborative work often entails more significant time investments compared to solitary endeavors. Faculty reflections, such as “Time - group work takes more time” and “Just adding another meeting to our schedule is just daunting,” underscore this reality. Such statements highlight the additional time and effort required for group coordination, discussions, and consensus-building, which are integral to collaborative projects but can also intensify the workload. This aspect is crucial in understanding the interpersonal dynamics of academic collaborations, where the efficiency and effectiveness of teamwork hinge on the ability to manage these increased time demands effectively.

The juxtaposition of individual autonomy in research with the collective responsibilities of teamwork presents a unique challenge in collaborative environments. Comments like “There is beauty to more independent work, which is that you have your own timelines” encapsulate the freedom and flexibility often associated with solo re-

search endeavors. However, this autonomy can be at odds with the structured timelines and shared accountability that characterize team projects. This tension reflects a significant aspect of interpersonal dynamics within academic collaborations, where individuals must negotiate their independent work preferences with the demands and expectations of the group.

The time demands theme emphasizes the importance of understanding that time constraints and external pressures vary among collaborators. Statements such as “Understanding what other faculty pressures are in different programs” and “People shouldn’t feel guilty about taking time to meet others” highlight the need for empathy and consideration toward colleagues’ schedules and commitments. This respect for each other’s time and workload is a pivotal aspect of interpersonal dynamics in collaborative work. It involves recognizing and accommodating the diverse responsibilities and constraints that each team member brings to the table, ensuring a collaborative atmosphere that is both productive and respectful of individual circumstances.

### **3.4 Conclusion**

In concluding the analysis of academic culture, institutional structures, and interpersonal dynamics, the reflection focuses on how these elements intertwine to shape the landscape of academic collaboration. The exploration of these themes has revealed a complex interplay between cultural norms, structural supports, and the intricacies of human interaction within the academic realm.

The academic culture, emphasizing achievements and faculty support, sets the stage for collaboration, often dictating its pace and direction. Institutional structures, including the pivotal role of infrastructure support, funding, and policies on workload and student involvement, either bolster or hinder collaborative efforts. These struc-

tures often serve as the framework within which collaborations must operate, setting the boundaries and providing the necessary resources.

Meanwhile, interpersonal dynamics, characterized by varying degrees of trust, respect, role clarity, and mutual interests, are the lifeblood of collaborative endeavors. Discussions with faculty members such as Allison Simler-Williamson, Cindy McCrea, and Juliette Tinker have illuminated the subtleties of these relationships. These dynamics are not merely supporting elements but are crucial in determining the success and longevity of collaborations. As the analysis transitions to the discussion section of the thesis, the aim is to delve deeper into how these themes interact and influence each other. The exploration will cover the implications of this interplay for the trajectories of research projects, the outcomes they yield, and the broader understanding of academic collaboration. This transition marks a shift from examining the constituent parts to understanding the whole, considering how academic culture, institutional structures, and interpersonal dynamics collectively shape the landscape of academic research.

### **Further Research**

Continuing (repeating) thematic analysis and adding in ethnographic methodology will help SNAP understand the reasons for the network topological changes. It would be beneficial to interview the GCs team leads or even all team members to enhance the interpretations of the analysis of the social networks.

## CHAPTER 4:

## CUPID

### 4.1 Collective Understanding of PI Data

The cumulative advantage is a primary driver for developing scientific stars (Mali *et al.*, 2012, p. 235), a term that refers to prominent scientists with disproportionate levels of collaborative interactions and recognition (Moody, 2004). Networks consist of actors (researchers) and the various types of relationships (ties) among them (Mali *et al.*, 2012, p. 216). Social Network Analysis (SNA) provides a framework for understanding network structures to the distribution of influence, focusing on the various relationships among actors within a network (Borgatti *et al.*, 2022, p. 2; Mali *et al.*, 2012, p. 216).

Probing into the dynamics of academic networks, a study by Skvoretz *et al.* (2023) explores the interplay between research and teaching discussions within three departments at three universities. Specifically, they investigate the interaction of research and teaching networks in the adoption of high-impact teaching practices (Skvoretz *et al.*, 2023). They found that the existence of a research tie between faculty enhances the likelihood of a teaching tie, showing the importance of entrainment in multiplex networks (Skvoretz *et al.*, 2023). This finding highlights the interconnectedness of research and teaching activities and their combined impact on academic practice.

Building on this interconnectedness, researcher networks demonstrate a modular structure that transcends disciplinary, sectoral, and geographical boundaries (Mali *et al.*, 2012, p. 219; Vacca *et al.*, 2015). These actors, or nodes, can be characterized by various categorical attributes, such as department affiliation, or continuous, like years of geographical distances (Mali *et al.*, 2012, p. 219). The relationship in this context, termed as ties or edges, connects researchers and can be quantified in multiple ways, including the frequency of interactions over a given period (Borgatti *et al.*, 2022, p. 2; Mali *et al.*, 2012, p. 216).

For example, Newman (2001) undertakes a comprehensive study of social networks, specifically focusing on scientific collaborations. Newman leverages the co-authorship of scientific papers as an unbiased and scalable measure for mapping social connections within the scientific community. Gathered data from multiple scientific databases, such as MEDLINE and the Los Alamos e-Print Archive, Newman (2001) created the network that tied each researcher in the network to all other researchers with whom they co-authored a paper within a five-year window (1995-1999). These ties interlink through common nodes, forming paths and, ultimately, a network. Within this network, frequently interacting actors may form a distinct subgroup (Borgatti *et al.*, 2022, p. 2). Newman (2001) found that researchers tend to collaborate with peers who have gained influence through numerous prior joint projects, following a pattern of preferential attachment (Mali *et al.*, 2012, p. 235-239; Vacca *et al.*, 2015, p. 284).

Co-authorship is a common type of relationship used to study scientific collaboration. In the book chapter by Mali *et al.* (2012), the authors also explore the complexities of scientific collaboration using co-authorship networks but highlight various

other collaborative activities, such as shared editorship, joint supervision of research projects, collaborative research proposal writing, participation in formal research programs, and the organization of scientific conferences (Mali *et al.*, 2012, p. 213). The extensive discussion on the research conducted by Mali *et al.*, particularly on the SNA methods used for scientific collaboration, is further elaborated in the methods section of this study.

## 4.2 Data

This study leverages Boise State’s historical grant proposal data from 2016 to 2020, sourced from DRED’s database. The dataset includes comprehensive records of grant applications detailing award status, faculty co-proposers, and their primary college affiliations without incorporating other demographic data. This data was transformed into network objects where sharing a grant proposal creates an edge between the researchers  $i$  and  $j$ . The study analyzes the collaborative structures over the entire period and annually, encompassing all proposals irrespective of award status.

The “College” attribute within the dataset encompasses a broad spectrum of academic divisions, including the College of Arts & Sciences, College of Business & Economics, College of Education, College of Engineering, College of Health Sciences, School of Public Service, and the College of Innovation and Design. The category labeled as “Other” aggregates entities that do not fall within these specified colleges, encompassing a diverse array of administrative and support units such as the Center for Teaching and Learning, the President’s Office, Provost and Vice President for Academic Affairs, departments like Public Policy & Administration, and various vice presidential offices responsible for finance, research, student affairs, campus operations, and general counsel, thereby ensuring a comprehensive representation of the

university's collaborative network.

The principal characteristics of the networks are summarized in Table 4.1. This table accounts for the total number of grant proposals submitted by Boise State researchers, distinguishing between collaborative and those submitted individually. It is important to note that the network analysis focuses exclusively on collaborative proposals; faculty who submitted proposals independently or did not submit any proposals during the specified period are considered network isolates, and due to the nature of network analysis statistical methods, such isolates are not included in this analysis.

The network size is determined by the count of faculty engaged in collaborative grant proposals within the specified time frame. Over five years, Boise State researchers submitted 2384 grant proposals, of which 766 were the result of collaborative efforts. The collaborative network over this period involved 446 faculty members, with an average of approximately 200 members participating annually. Edges represent the total number of collaborative ties, with a notable variance from 335 to 406 annually. Despite 2020 having the fewest co-proposers and overall proposals, it showed a disproportionately high number of edges (360), indicating a dense collaboration pattern among the participating faculty members that year.

Acknowledging the complexities of discerning roles and directionality in collaborative grant proposals, the analysis treats the network as undirected to capture all co-author connections. This methodological choice ensures the inclusion of all collaborative ties, circumventing the limitations of a directed analysis that might only consider PI to Co-PI relationships and overlook interactions among Co-PIs. By treating the network as undirected, the analysis avoids imposing a hierarchical structure

**Table 4.1: Main Descriptors of Historical Grant Proposal Networks**

| Year | Network Size | Proposal Count | Collaborative Proposals | Edges |
|------|--------------|----------------|-------------------------|-------|
| 2016 | 207          | 457            | 166                     | 335   |
| 2017 | 213          | 502            | 159                     | 355   |
| 2018 | 214          | 537            | 174                     | 406   |
| 2019 | 213          | 480            | 155                     | 339   |
| 2020 | 169          | 408            | 112                     | 360   |
| 5yr  | 446          | 2384           | 766                     | 1284  |

on the collaboration, thereby encompassing a broader view of joint efforts in proposal development.

### 4.3 Methods

In their work, Mali *et al.* (2012, p. 216) delineate the core principles of contemporary SNA as delineated by Freeman (2004), which include analyzing the structure of actors in social networks, employing empirical data systematically, utilizing network visualizations, and relying on a basis of formal mathematical and computational methodologies. By leveraging SNA, this study analyzes the web of grant proposal collaboration, highlighting how relationships and network structures contribute to the development of scientific work. Using RStudio, an integrated development environment for R, enhances the analytical process by facilitating data management, statistical analysis, and graphical representation of networks (RStudio Team, 2020). Network visualizations are created in the igraph package (Csárdi *et al.*, 2024), while node and network metrics are calculated with the network and sna packages (Butts *et al.*, 2023; Butts, 2023), and exponential random graph models are employed using

the network and ergm packages (Handcock *et al.*, 2023). This approach enables detailed descriptions of Boise State's grant proposal collaboration networks and their evolution between 2016 and 2020.

### 4.3.1 Preferential Attachment

The principle of preferential attachment suggests that nodes occupying central positions within research networks are more likely to be chosen as collaborators, as outlined by Vacca *et al.* (2015). This phenomenon, when occurring between two central scholars, embodies the notion of cumulative advantage. Furthermore, when peripheral researchers seek out collaborations with well-established academics, the dynamics may reflect a mentor-mentee relationship, indicating a hierarchical structure of knowledge exchange and professional development within the network.

To explore the dynamics of preferential attachment within academic networks, this thesis utilizes centrality metrics as analytical tools. The local property of a node in the network is degree centrality, defined as the number of ties a node has (Mali *et al.*, 2012, p. 214; Borgatti *et al.*, 2022, p. 171). A high degree takes the shape of a star, where one node has many ties to other nodes compared to most other nodes in the network. Its interpretation can vary based on the nature of these ties (Borgatti *et al.*, 2022, p. 172). A star structure in team science networks may indicate a significant inequality in collaborative offers, as few scientists or scholars receive disproportionate offers to collaborate (Moody, 2004). The cumulative advantage in science posits that scientists already recognized for their contributions are more likely to gain further recognition and resources (Mali *et al.*, 2012, p. 235). This concept, drawing parallels to the biblical passage in Matthew's Gospel and referred to as "The Matthew Effect," implies a disparity in the distribution of resources and opportunities within the scientific

community, where established researchers gain disproportionately more funding and power while emerging scientists face challenges in achieving recognition and success (Mali *et al.*, 2012, p. 235-236). This concept highlights how normal social behaviors can thwart the GCs' investment goal to expand research opportunities across campus (Boise State University, 2024, See goal 4).

Networks formed through preferential attachment, new ties occur because of the presence of other ties (Lusher *et al.*, 2013, p. 26), suggest a scale-free structure characterized by a power-law degree distribution where burgeoning scientists tend to collaborate with established scientific stars. Preferential attachment may reflect the principle of cumulative advantage in science (Mali *et al.*, 2012, p. 215; Vacca *et al.*, 2015) where this scale-free structure indicates a hierarchical network dominated by a few highly connected individuals or "hubs" (Mali *et al.*, 2012, p. 215, 236). One method used to examine the presence of scientific stars is the **degree distribution**. A declining degree distribution indicates that most network members have few ties, and few members possess many ties (Harris, 2014, p. 17).

Betweenness centrality quantifies the frequency with which a node appears along the shortest paths between other pairs of nodes in the network (Borgatti *et al.*, 2022, p. 182). This metric not only showcases a node's capacity to act as a pivotal broker within the network but also its potential to influence the allocation of critical scientific resources, including research funding, teaching positions, and publication opportunities (Mali *et al.*, 2012, p. 236). Such brokers, by virtue of their key decision-making roles within scientific institutions, can significantly impact who gains access to valuable network assets, especially by facilitating or restricting the integration of peripheral members into the core collaborative framework. This role is particularly relevant

in co-authorship networks, where betweenness centrality serves as an indicator of an individual's ability to foster diversity and promote multi-disciplinary collaboration (Leydesdorff *et al.*, 2019, p. 258, 266). By bridging various knowledge domains, individuals with high betweenness centrality not only contribute to the interdisciplinary nature of scientific research but also possess the power to shape the research landscape by directing resources and opportunities towards emerging areas of inquiry and new collaborators.

This thesis investigates the structural implications of key brokers on interdisciplinary research collaboration dynamics. Mapping the **betweenness distribution** across the network provides a detailed view of how these pivotal individuals serve as bridges across disciplinary gaps and may enhance access to resources and collaborative opportunities. This investigation highlights the role of network centrality in fostering an interconnected research environment, emphasizing the balance between sustaining existing connections and fostering new, interdisciplinary collaborations. The study aims to pinpoint areas where strategic enhancements to network connectivity could support the inclusion of a wider range of academic contributions, thereby strengthening the Grand Challenges initiative's scope and effectiveness.

The ideal scenario posits a network replete of few high-betweenness brokers; instead, most faculty members are directly connected to the core network (Mali *et al.*, 2012, p. 236). A more egalitarian structure where knowledge and resources flow more freely among the members is a highly connected network. The **connectedness** score illuminates the level of structural cohesion (Borgatti *et al.*, 2022, p. 201-203). Comparing the connectedness across each year's network depicts the change in structural cohesion of the grant proposal network over time. Analysis from degree distribution

and connectedness could be used to intentionally connect researchers across diverse modules, such as spanning structural holes and counterbalancing preferential attachment, as Vacca *et al.* (2015) showcase.

While connectedness highlights the structural cohesion within the grant proposal network, revealing the network's integrative capacity over time, density offers a more granular perspective on interconnectivity. **Density** is a fundamental concept that offers insight into a network's structure and interconnectivity. Norton *et al.* (2017, p. 6) define density as the "ratio of the number of actual links to the number of possible links in the network." This ratio provides a quantitative measure of how interconnected the individuals within the network are. Borgatti *et al.* (2022, p. 195-196) further explain that density indicates the likelihood of any two individuals within the network being connected.

The analysis of preferential attachment within Boise State's grant proposal network underscores the significance of central nodes or 'scientific stars' in shaping collaborative patterns, highlighting the cumulative advantage these nodes possess in attracting collaboration. This exploration not only illuminates the hierarchical dynamics within academic networks but also sets the stage for examining interdisciplinary collaboration. The subsequent section shifts focus to measuring interdisciplinary collaboration, utilizing a combination of network analysis techniques and interdisciplinary distance metrics to assess the breadth and depth of cross-disciplinary research efforts and their impact on fostering innovative, impactful scientific inquiry.

#### 4.3.2 Interdisciplinary Co-Proposors

Measuring interdisciplinary collaboration is at the core of this thesis and was heavily explored in the literature review section 2.2. Adopting similar terminology proposed

by Bolger (2021) to assess the degree of interdisciplinary research, the grant proposal network's disciplinary distance is defined as super-disciplines when researchers from different colleges share a grant proposal together. Co-proposers from the same college are either collaborating within a discipline or within a short distance of their discipline.

One method this thesis employs to investigate the degree of interdisciplinary co-proposers is to visually inspect the network by college affiliation. Research specialties are a cluster of collaborating scientists responsible for producing many innovative concepts and ideas (Moody, 2004; Vacca *et al.*, 2015). Collaboration within disciplines often leads to the emergence of distinct clusters within research collaboration networks, indicative of a small-world network structure marked by high local clustering and minimal steps between clusters (Mali *et al.*, 2012, p. 215; Vacca *et al.*, 2015). This structure contrasts with a cohesive core, characterized by an increasing trend of authors from various disciplines collaborating (Moody, 2004). Therefore, the **network visualization** analysis shifts to examining college clustering, illuminating possible disciplinary and short-distance clustering.

In addition to network visualizations, network statistics can illuminate interdisciplinary patterns. In small-world networks, there is a notable pattern of dense local connections among actors, yet these actors are separated by only a few intermediary steps (Moody, 2004). This structure contrasts with a cohesive core, characterized by an increasing trend of authors from various disciplines collaborating (Moody, 2004). The **clustering coefficient**, a measure reflecting the network's tendency for triadic closure, is calculated by the ratio of the actual number of closed triangles to the potential number of triads that could contain at least two ties (Goodreau *et al.*, 2009).

Interestingly, a network's propensity for clustering often corresponds with increased path lengths, suggesting that as clusters become more defined, the distance between separate clusters can grow (Mali *et al.*, 2012, p. 199). Networks with clusters that cross super-disciplines form "invisible colleges" that drive the intellectual and creative output of the scientific community (Mali *et al.*, 2012, p. 236).

The application of Exponential Random Graph Models (ERGMs), discussed below, allows for further dissecting of these interdisciplinary collaborations among other important variables, factoring in both the attributes of individual actors and the overarching network configurations.

### 4.3.3 Exponential Random Graph Models

ERGMs represent a transformative advancement in SNA, providing a robust statistical framework for modeling network data (Mali *et al.*, 2012, p. 218). ERGMs are particularly useful because they allow for the modeling of network structures (endogenous effects) while controlling for individual attributes (exogenous variables), thus enabling researchers to disentangle the effects of actor attributes from the structural patterns of the network (Lusher *et al.*, 2013, p. 10, 23-24, 91-92). In ERGMs, the existence of ties between individuals (outcome variable) is determined by a combination of their attributes (independent variables) and the existing patterns of connections within the network (Lusher *et al.*, 2013, p. 51). These models, functioning as an auto-logistic regression, treat tie variables as dependent on the entire graph structure, thus allowing for a comprehensive understanding of network dynamics (Duxbury, 2021, p. 4-5).

The essence of ERGMs lies in their ability to capture and quantify recurring patterns or configurations within a network, which occur with greater frequency than would be expected by chance (Harris, 2014, p. 33). Such configurations are

broad-ranging, enabling the application of ERGMs across diverse contexts. A positive parameter value within these models signifies a higher likelihood of a particular configuration's occurrence in the network (Caimo & Gollini, 2020, p. 2).

This study employs curved ERGMs, as delineated by (Hunter *et al.*, 2008a). The probability mass function for an ERGM, which estimates the probability of ( $\text{Pr}$ ) observing a network  $Y$ , with ties  $y_{ij}$  connecting actors  $i$  and  $j$ , as a function of actor-level exogenous characteristics and graph statistics, is formalized as:

$$\text{Pr}(Y = y|z(y, x)) = \frac{\exp(\theta^T z(y, x))}{\kappa(\theta)}, \quad (4.1)$$

Here,  $\theta$  denotes the parameter vector, also known as the Maximum Likelihood Estimate (MLE) (Lusher *et al.*, 2013, p. 147). The vector  $z(y, x)$  incorporates both exogenous characteristics  $x$  and endogenous graph statistics calculated from  $Y$  (Duxbury, 2021). The term  $\kappa(\theta)$  represents a normalizing constant, guaranteeing that the sum of the probabilities across all possible networks equals one (Duxbury, 2021). The parameters reflect the change in the log-odds of a tie  $ij$  following a unit change in a focal covariate, conditional on the other covariates in the model (Duxbury, 2021, p. 5).

The computation of the normalizing constant  $\kappa(\theta)$  presents a challenge due to its intractability for most networks of interest (Krivitsky *et al.*, 2021, p. 35). As such, it is often approximated through Markov chain Monte Carlo (MCMC) methods, which involve sampling from a distribution of possible networks to estimate the maximum likelihood (Duxbury, 2021; Hunter *et al.*, 2008b). The model's foundational assumptions include the representation of the observed network as a reliable sample from the underlying stochastic process, adherence to the likelihood principle, and the suitabil-

ity of the likelihood formulation for network data modeling (Duxbury, 2021). The likelihood principle specifically posits that all information pertinent to parameter estimation is encapsulated within the likelihood function (Duxbury, 2021).

Moreover, the conditional form of ERGMs, akin to logistic regression and expressed by a cumulative distribution function, offers a tie-level interpretation, as shown in the equation below:

$$p_{ij} = \frac{\exp(\theta_{\text{endogenous}}^T \delta_{ij}^+(y) + \theta_{\text{exogenous}}^T x_{ij})}{1 + \exp(\theta_{\text{endogenous}}^T \delta_{ij}^+(y) + \theta_{\text{exogenous}}^T x_{ij})} \quad (4.2)$$

In this equation,  $\delta_{ij}^+$  symbolizes the alteration in the parameterized graph statistic that results when the existence of a tie  $y_{ij}$  shifts from absence (0) to presence (1) (Duxbury, 2021).

The ERGMs developed in this study were crafted to reflect key theoretical premises about social networks, including their local emergence, the impact of actor attributes and external factors on network ties, and the structured, stochastic nature of these ties, as posited by Lusher *et al.* (2013, p. 10). The stepwise integration of nodal attribute terms and the evaluation of model fit using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were guided by these principles, ensuring the models captured the complexity of social networks while remaining parsimonious and theoretically aligned. This approach facilitated the prioritization of terms that directly contribute to an understanding of the underlying structural processes within networks, as evidenced by changes in AIC or BIC values Harris (2014, p. 63).<sup>1</sup>

In this study, the evaluation of network ties and their formation mechanisms

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<sup>1</sup>Each ERGM summary is provided in Appendix F.

employs numerical approximations for log-likelihood, addressing the computational challenge posed by the intractability of the normalizing constant. This technique facilitates the practical application of ERGMs (Lusher *et al.*, 2013, p. 160). The significance of model parameters, notably the edges term, which is analogous to the intercept in logistic regression, is assessed using the Wald test. This test calculates the ratio of the parameter estimate to its approximate standard error, with values outside the -2 to 2 range signaling significant deviations from zero, thereby providing a rigorous evaluation of the network's structured and non-random formation dynamics (Lusher *et al.*, 2013, p. 157).

The employment of numerical approximations for log-likelihood is crucial for addressing the complexity of network data, enabling the exploration of the Direct Network-attribute-dependent assumption, which posits that individual attributes within a network become conditionally interdependent upon the establishment of direct ties (Lusher *et al.*, 2013, p. 107-108). This underscores the need for sophisticated models to elucidate the intricate dynamics of attribute interplay and tie formation. This assumption highlights the intertwined influence of local network structures and individual characteristics on the process of tie formation, emphasizing the complex interplay between the social environment and individual attributes in shaping network connections (Lusher *et al.*, 2013, p. 107-108); (Harris, 2014, p. 52-53); (Lusher *et al.*, 2013, p. 19). To contextualize the Direct Network-attribute-dependent assumption within the network's actual structure, the null model serves as a baseline, capturing the network's propensity to form edges while providing a reference point for assessing the influence of local structures and individual characteristics on tie formation.

The null model of an undirected network, described by Harris (2014, p. 39-47), only

includes a single edges term representing the number of connections in the network. This model sets a baseline by capturing the network's overall propensity to form edges (its density) while disregarding other structural features (Lusher *et al.*, 2013, p. 109). The statistical significance of the edges term in more complex ERGMs, implies that the network's structure is not random but is likely influenced by underlying principles (Harris, 2014). By employing the null model, which includes only a single edges term to represent network connections, this study establishes a baseline for network density, enabling a nuanced comparison with more complex ERGMs, such as the addition of dyadic independence terms.

### Dyadic Independence Terms

Exogenous variables, independent of the network's structure, significantly influence the formation of ties by embodying attributes external to the network dynamics (Lusher *et al.*, 2013, p. 23, 26, 91). The Independence Attribute assumption, where individual attributes  $Y_i$  and  $Y_j$  operate independently without the network's influence on their distribution, negates the possibility of social influence effects (Lusher *et al.*, 2013, p. 106-107). Conversely, the Covariate-Dependent assumption posits that an actor's attribute is conditionally influenced by other covariates associated with that same actor—a cornerstone of traditional logistic regression models (Lusher *et al.*, 2013, p. 108). A key example of an exogenous factor is homophily, which describes the propensity for nodes with similar attributes to connect, illustrating how specific attributes drive tie formation.

Goodreau *et al.* (2009) examine friendship networks, demonstrating the use of several ERGM terms. They explain selective mixing as the propensity of individuals

to form connections based on shared attributes (Goodreau *et al.*, 2009). They define **uniform homophily** as the tendency to form ties with others who have similar (homophily) or different (heterophily) attributes (Goodreau *et al.*, 2009).

To evaluate the grant proposal network for long-distance interdisciplinary collaboration (Bolger, 2021), uniform homophily was first investigated using the *nodematch* term. The ‘*diff = TRUE*’ argument separates parameters for each college category, allowing the model to capture the propensity for faculty within the same college to co-propose more than would be expected by chance. Each college’s statistics quantify the extent of collaborative grant proposal engagement among faculty within the same college. An affirmative coefficient indicates homophily, signifying discipline-centric or “short-distance” interdisciplinary collaborations. Conversely, a negative coefficient implies heterophily, suggesting “long-distance” interdisciplinary collaborations. The working hypothesis posits that faculty members tend to co-propose with other faculty members within their own college.

Another selective mixing term that Goodreau *et al.* (2009) describes is **differential homophily**, a propensity to form ties specific to individual categories. The likelihood of forming a tie depends on a particular attribute that differs across various categories of that attribute. As an illustration, Lane *et al.* (2020), investigated the use of Evidence-based Instructional Practices (EBIPs) in college STEM courses, examining the communication ties relative to EBIP usage among instructors. Their findings revealed distinct interaction patterns based on EBIP familiarity, suggesting a nuanced picture of knowledge diffusion (Lane *et al.*, 2020). Similarly, this study assigns a quartile attribute based on co-proposal counts to explore preferential attachment and mentorship using differential homophily within the grant proposal network.

The primary aim of this term’s investigation is to determine the propensity of researchers to engage in grant proposal collaborations with peers who exhibit similar levels of co-proposal activity. The allocation of faculty members into quartiles based on their proposal submission frequency serves as the basis for this analysis, with the first quartile representing the lowest frequency of proposals and the fourth the highest. Utilizing the *nodemix* term, this study delves into the concept of differential homophily among these quartiles, providing a nuanced understanding of collaboration patterns within the academic network. This approach allows for the exploration of preferential attachment, hypothesizing that researchers with a high volume of proposals may be more likely to collaborate with each other, a phenomenon that could illustrate a “rich getting richer” dynamic as described by Mali *et al.* (2012, p. 233).

High proposers collaborating signify this cumulative advantage in the scientific arena because well-established researchers not only form powerful coalitions but also disproportionately accrue additional recognition and resources, as discussed by Sonnenwald (2007, p. 8) and Disis & Slattery (2010). This scenario could manifest disparities in the distribution of resources and opportunities within the scientific community. On the other hand, frequent collaborations between high and low proposal submitters could indicate mentorship dynamics or varying needs for resources, reflecting the diverse motivations and strategic objectives that underpin academic partnerships. Such complexity underscores the multifaceted nature of these collaborations, influenced by an array of factors that extend beyond the simplistic binary of experience or establishment, thereby enriching the tapestry of scientific inquiry and resource sharing across the community.

Transitioning from the exploration of selective mixing, this study further exam-

ines the influence of individual characteristics on actor activity levels (Lusher *et al.*, 2013, p. 110). **Sociality** is defined as the inherent tendency of individuals to establish friendships, influenced by an array of factors, including personality traits, sociodemographic characteristics, or external circumstances (Goodreau *et al.*, 2009). Goodreau *et al.* (2009) view sociality as a social process that significantly contributes to the outcome, specifically in terms of degree. The impact of a faculty member's college affiliation on their propensity to co-propose is examined using the term *nodelfactor*. This term captures the network position effects (Lusher *et al.*, 2013, p. 110), particularly focusing on the impact of categorical nodal attributes on network formation (Krivitsky *et al.*, 2021). This thesis analyzes how the structural positions associated with specific college affiliations influence the likelihood of tie formation in the network (Lusher *et al.*, 2013, p. 110), quantifying the likelihood of faculty within a specific college to co-propose on grants in comparison to a reference college.

Dyadic independence ERGMs, which include only exogenous factors, are akin to traditional logistic regression (Goodreau *et al.*, 2009). The probability of a tie is contingent solely upon the attributes of the actors involved, with tie values being mutually exclusive (Goodreau *et al.*, 2009). This is congruent with maximum pseudolikelihood estimation (MPLE) mirroring maximum likelihood estimation (Goodreau *et al.*, 2009).

The assessment of model fit through the AIC, and BIC is further complemented by comparing network characteristics between the observed data and simulated networks, adhering to the goodness of fit methodology outlined by Harris (2014, p. 63-70). This comparison highlights a significant misalignment in the degree distribution and the distribution of edgewise-shared partners, emphasizing the need to integrate dyadic

dependence terms into the analysis.

### Dyadic Dependence Terms

Conventional statistical models, which assume the independence of observations, fail to capture the intricacies of human social behavior that is inherently multifaceted and driven by intentions (Lusher *et al.*, 2013). The importance of endogenous, tie-based effects lies in their alignment with specific social science theories that posit a particular kind of dependency on local configurations (Lusher *et al.*, 2013, p. 19, 102). The formation of new ties is dependent on the existence of other local ties, illustrating the interconnectedness of social relationships (Lusher *et al.*, 2013, p. 91-92, 102). For example, the probability of a tie forming between two individuals is often contingent on shared connections within the network, indicative of a predisposition towards triadic closure (Lusher *et al.*, 2013, p. 69-71).

The **geometrically weighted edgewise shared partners** (GWESP) and geometrically weighted dyadwise shared partners (GWDSP) terms capture the concept of transitivity (the concept that friends of my friend are also my friend (Okraku *et al.*, 2017, p. 179) in network structures, underscoring how an individual's network position and the transitivity path closure of their relationships—evidenced by paths of length two and triangle formations—inform their attributes' dependence on specific network connections (Lusher *et al.*, 2013, p. 107). GWESP tests how the presence of shared partners between two individuals influences the formation of new ties (Goodreau *et al.*, 2009; Lusher *et al.*, 2013, p. 69-71). Unlike simple triad closure, which might occur through incidental contact, transitivity reflects a deeper process where shared friends or collaborators lead to direct connections based on perceived

social value or affinity (Goodreau *et al.*, 2009). By incorporating the GWESP term into the models, the network's triangles is quantitatively assessed, evaluating how an existing shared co-proposal influences the formation of additional co-proposals.

As Harris (2014, p. 85) explains, a statistically significant coefficient implies that the likelihood of tie formation between two individuals is higher than expected by chance, given all other factors are held constant. In other words, shared partners significantly increase the chances of two faculty members collaborating on a grant proposal. If the GWESP coefficient were negative, it would suggest a network where shared partnerships are less likely to lead to new ties, possibly indicating a network less driven by collaborative triangles (Harris, 2014, p. 85). In the context of the grant proposal network, a significant positive GWESP coefficient would support the idea that faculty are more likely to co-propose with others who have mutual collaborators, reflecting a tightly knit community where collaboration is fostered through established connections (Harris, 2014, p. 85). This pattern is characteristic of networks where knowledge and resources are often exchanged within well-defined local triangles, indicating disciplinary research or thematic communities (Mali *et al.*, 2012, p. 236).

Exploring the concept of preferential attachment within the grant network, this study delves into the **geometrically weighted degree** (GWD) to understand how connections impact network behavior. Under the Network-Dependent assumption, it is recognized that an individual's likelihood of forming new ties is not only based on their existing connections but also significantly influenced by the network's overall structure, as reflected in star configurations which indicate the level of an individual's direct connections within the network (Lusher *et al.*, 2013, p. 107). To accurately

model this dynamic, GWD parameters, incorporating alternating signs for varying star counts, are utilized to balance the representation of nodes across the spectrum of connectivity, ensuring that the model effectively captures the distribution of nodes with different tie counts without skewing towards overly dense or sparse network configurations (Lusher *et al.*, 2013, p. 65-66). This approach to modeling, by adjusting the weight given to nodes based on their degree, highlights the GWD's role in mitigating sudden shifts in network density and providing insights into the network's structural tendencies driven by social interactions. The significance of GWD parameters in this context underscores the network structure's complexity and the critical role of preferential attachment and individual attributes in shaping network dynamics.

GWD models the degree distribution within networks, emphasizing the significance of higher-degree nodes by assigning them more weight. Levy (2016) emphasizes that GWD is instrumental in revealing degree popularity. A positive estimate is indicative of edge dispersion across the network (Levy, 2016), suggesting a more equitable distribution of ties across the network. This indicates a network characterized by a greater number of highly connected nodes (Harris, 2014, p. 83). A negative estimate reveals concentrated centralization (Levy, 2016), a condition where few researchers have a disproportionately high number of connections with other grant proposers. This could imply a tendency towards preferential attachment (Harris, 2014, p. 85), where certain nodes act as hubs within the network (Mali *et al.*, 2012, p. 236). However, the nuances of these coefficients should be interpreted with caution due to the intricate way a single tie can affect the overall shared partner distribution within the network (Harris, 2014, p. 85).

Geometrically weighted terms in ERGMs capture the self-organization of social networks by accounting for the dependency structure among ties. These geometric terms reflect high-order dependencies, introducing challenges in estimating model parameters (Lusher *et al.*, 2013, p. 160-162; Hunter *et al.*, 2008b). Models with geometrically weighted terms require MCMC simulation methods to address model degeneracy (Lusher *et al.*, 2013, p. 160-162; Hunter *et al.*, 2008b, p. 254). MCMC works by generating a sample of possible networks that could theoretically have generated the observed data, allowing for the estimation of parameters that best represent the underlying social processes shaping the network (Harris, 2014, p. 71; Hunter *et al.*, 2008b, p. 254).

## Model Selection

To mitigate the risk of model nonconvergence and ensure robustness in the ERGMs, adherence to the methodological parameters recommended by Harris (2014) was maintained. The MCMC sample size, dictating the count of networks to be sampled, was established at 10,000. The MCMC burn-in period, which denotes the number of initial samples to be discarded to allow the chain to reach equilibrium, was set to 100,000. Additionally, the MCMC interval, defining the sequence gap between samples, was fixed at 1,000 to minimize autocorrelation. A seed value of 567 was selected to facilitate the reproducibility of the model.

In line with Harris (2014) 's guidance, a stepwise methodology was employed to calibrate the decay parameters for the geometrically weighted terms, commencing with a baseline of 0.1. Upon observing the non-convergence of the GWDSP term at

the initial decay parameter, it was consequently omitted from the subsequent models.<sup>2</sup> Both the GWESP and GWD terms underwent a systematic incrementation of their decay parameters by 0.1 in each iteration of model refinement. The final iteration, which yielded the lowest AIC of 8782 and BIC of 9038, incorporated decay parameters of 3.5 for these geometrically weighted terms.

MCMC diagnostics showed that the model converged.<sup>3</sup> The goodness-of-fit evaluation for the ERGM, following Hunter *et al.* (2008b), demonstrates an alignment with observed data, particularly in capturing the behavior of highly connected nodes and the network's transitivity tendencies. While the degree distribution's fit suggests that the model effectively represents the network's tail behavior, indicating accurate replication of highly connected nodes, discrepancies at lower degrees highlight potential refinement areas. Additionally, the fit for edgewise shared partner distribution and minimum geodesic distance provides insights into the network's cohesion and navigability, albeit with room for improvement in modeling less connected nodes' connectivity. These diagnostics, supported by Monte Carlo p-values, affirm the model's overall adequacy in mirroring structural patterns, guiding future refinements to enhance descriptive and predictive validity regarding academic collaborative behaviors.<sup>4</sup>

## 4.4 Analysis

The analysis section of this thesis presents a comprehensive examination of Boise State grant proposal networks, utilizing a multifaceted analytical approach that com-

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<sup>2</sup>The distribution of the observed network's DSP compared to random network DSP are similar as seen in Histogram of DSP

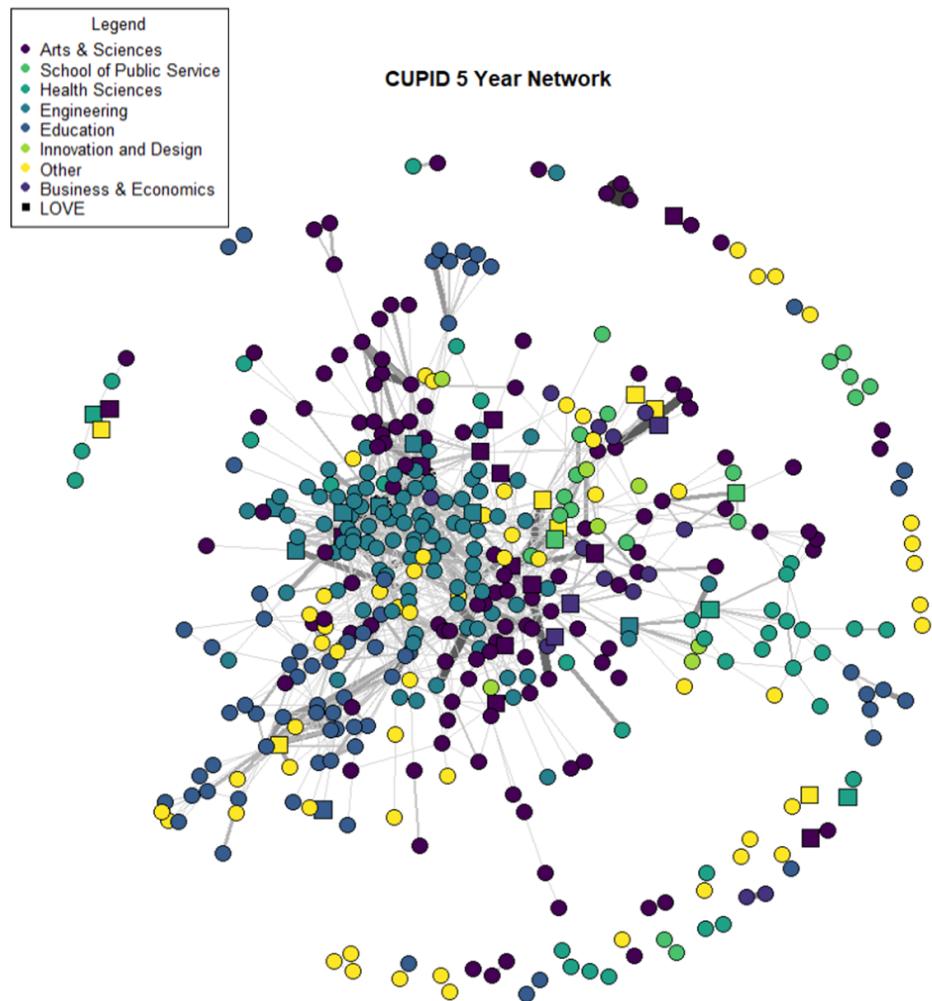
<sup>3</sup>The MCMC diagnostic plots can be found in Appendix C.

<sup>4</sup>Goodness Of Fit Plots are available in Appendix D.

bines network visualizations, network metrics, and ERGM results. By meticulously analyzing these different aspects, the thesis aims to unveil the underlying patterns, structures, and dynamics that characterize preferential attachment, interdisciplinary collaboration, and other time-based effects. Network visualizations offer a graphical representation of the collaborative ties, visually highlighting patterns of super-discipline co-proposers. Network metrics provide quantitative insights into the structural properties of these networks, including centrality measures and clustering coefficients. Lastly, ERGM results offer a statistical modeling perspective, identifying significant factors influencing the formation of collaborative ties. Together, these analyses aim to provide a holistic understanding of how faculty members at Boise State engage in grant proposal collaborations, contributing to the broader goals of enhancing collaborative practices and fostering innovative scientific inquiry.

## **Networks Visualized**

Network visualizations offer a graphical representation of the collaborative dynamics within the institution's colleges, highlighting key actors, cohesive subgroups, and the potential for interdisciplinary collaboration. These visualizations reveal modular structures, which are indicative of distinct groups of researchers that are not interconnected, thereby suggesting opportunities for fostering interdisciplinary collaboration. It is important to note that the physical proximity of nodes on the graph suggests a higher frequency of shared ties, enhancing our understanding of collaboration density. In these graphs, a line between nodes signifies co-authorship of a collaborative grant proposal, providing a clear indication of the existing research partnerships and the potential for developing new interdisciplinary linkages.



**Figure 4.1:** The comprehensive network visualization, which encapsulates five years of collaborative grant proposals, displays structural characteristics intrinsic to the network's architecture. Utilizing the Fruchterman-Reingold algorithm, the layout accentuates the clustering of nodes based on the weighted edges (Csárdi *et al.*, 2024), which represent the number of shared grant proposals.

Figure 4.1 shows Boise State’s collaborative grant proposal aggregated network between 2016 and 2020.<sup>5</sup> Central to the network is a densely interconnected core cluster, suggesting an intensive collaboration level within and across the represented colleges. Surrounding this nucleus, peripheral nodes are observed, characterized by less dense connections, which may imply either specialized domains of research with fewer collaborative proposals or more occasional partnerships.

The visualization’s edges are weighted to reflect the number of shared grant proposals, with thicker lines indicating a higher number of collaborations. Utilizing the Fruchterman-Reingold algorithm, the layout accentuates the clustering of nodes based on the weighted edges (Csárdi *et al.*, 2024), which represent the number of shared grant proposals. Such visual weight differentiation aids in identifying prominent collaborative dyads and the hierarchical structure of collaboration intensity within the network.

Within the primary cluster, a sub-cluster comprising dark blue nodes, signifying the College of Education, intermingled with yellow nodes, categorized as ‘other’ affiliations, is evident in the lower left quadrant. This configuration may suggest a trend towards collaborative synergy within these groups, potentially driven by shared research foci or complementary objectives. The College of Engineering, indicated by turquoise nodes, is centrally and prominently located within the upper part of the main cluster, highlighting its significant role in collaborative ventures.

Off to the right and extending outward, a smaller, distinct sub-cluster is noticeable, comprising nodes associated with the health sciences. This group’s peripheral positioning may be indicative of a more insular collaboration pattern within this disci-

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<sup>5</sup>Detailed network visualizations representing the collaborative grant proposals for each individual year within the 2016 to 2020 period have been compiled and can be found in Appendix A.

pline, with occasional forays into interdisciplinary projects, as evidenced by its points of connection to the main cluster.

The College of Arts and Sciences, depicted by dark purple nodes, exhibits a dual clustering within the main group, with nodes concentrated in both the upper and lower mid-sections. This suggests a multi-pronged role in bridging various disciplines, notably with the College of Engineering, where a notable degree of intermixing is observed.

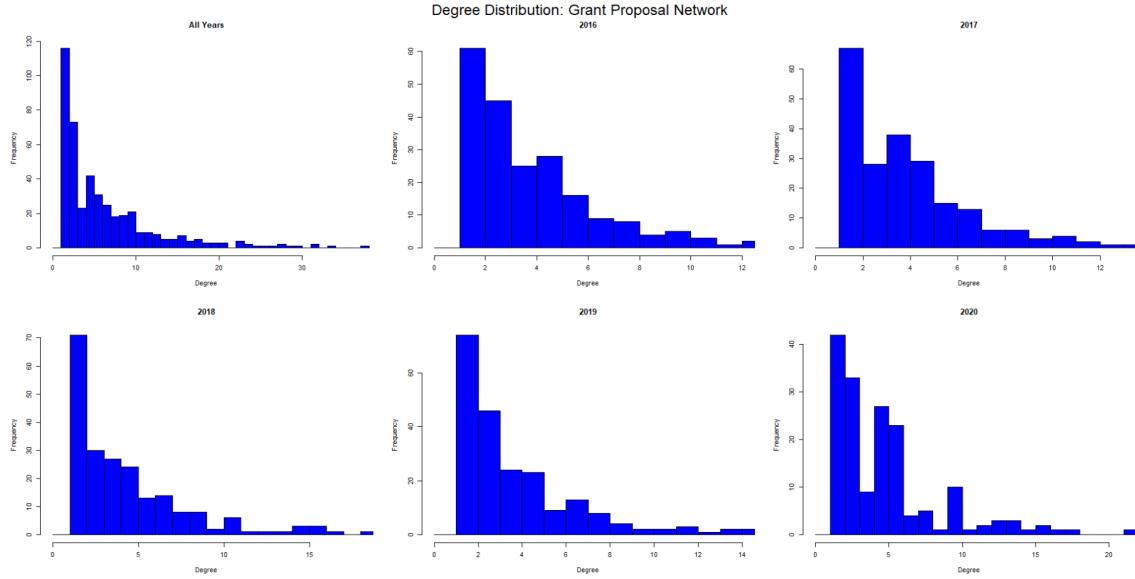
#### 4.4.1 Network Metrics

This subsection identifies “Scientific Stars,” understanding the role of “Brokers,” and assessing “Structural Cohesion.” Each of these network characteristics provides a lens through which the nature and dynamics of interdisciplinary collaboration can be evaluated.

##### Scientific Stars

In this section, scientific stars are identified by analyzing the degree distribution within the network, a method that highlights the uneven distribution of collaborative efforts. Defined as highly recognized scientists for their vast collaborations and achievements, these stars emerge from a network shaped by preferential attachment resulting in cumulative advantage. The preferential attachment mechanism suggests young scientists gravitate towards established figures, potentially creating a scale-free network (Mali *et al.*, 2012, p. 232). Cumulative advantage describes the phenomenon where well-recognized scientists gain further recognition, amplifying disparities in collaboration and acknowledgment (Mali *et al.*, 2012, p. 235). Thus, the degree distribution analysis serves as a tool to examine the hierarchical structure formed by

these scientific stars, revealing patterns of collaboration concentration among a few faculty members and illustrating the network's structural dynamics.<sup>6</sup>



**Figure 4.2:** Degree distribution histograms of the CUPID grant proposal networks for each year from 2016 to 2020 and cumulatively across all years. The horizontal axis represents the degree value for the researchers, and the vertical axis shows the frequency of those degree values for the researchers within the network. The right-skewed distributions across all histograms indicate a pattern where most faculty members have relatively few co-proposers, while a smaller number have a high degree of collaborative proposals, suggesting the presence of scientific stars within the network and a potential scale-free, hierarchical structure characterized by cumulative advantage.

The histograms in Figure 4.2 represent the degree distribution of nodes within the CUPID historical grant proposal networks, spanning individual years and cumulatively across all years. Degree, the metric plotted on the horizontal axis, indicates the number of grant proposals a particular researcher has within the network. Nodes with higher degree are pivotal, often acting as central figures in the network akin to scientific stars.

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<sup>6</sup>The concept of cumulative advantage can also be quantified using the Gini ratio of degree centrality. This measurement option is elaborated upon in Chapter 6. The Lorenz curves—based on Gini coefficient calculations—visually represent the distribution of degree centrality. Further analysis is necessary, refer to Appendix B.

Across all histograms, there is a pronounced right-skewed distribution, with a high frequency of nodes having a low degree and a significantly smaller frequency of nodes with a high degree. This skewness suggests that while most faculty members are involved in grant proposals with a limited number of co-proposers, a select few have extensive collaborative ties, supporting the concept of a scale-free network. Such networks are characterized by the presence of hubs—highly connected nodes—which are indicative of a hierarchical structure (Mali *et al.*, 2012, p. 236).

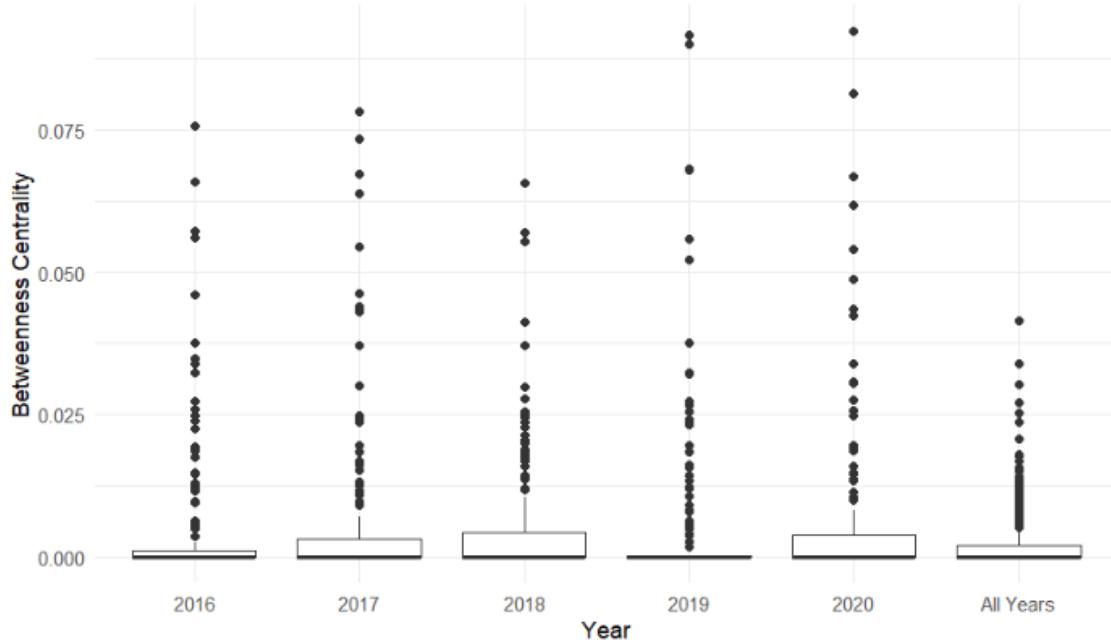
This pattern also aligns with the principle that emerging scientists often seek collaboration with these scientific stars, creating a network dynamic where few members hold the majority of connections (Vacca *et al.*, 2015).

The declining nature of the degree distribution within these histograms, where the majority of network members have few ties, and a minority have many, is emblematic of networks where the cumulative advantage is at play (Harris, 2014, p. 17). The presence of this declining degree distribution makes the network a suitable candidate for applying the ERGM term GWD, which can further elucidate the underlying processes of cumulative advantage and mentorship within the research network.

## Brokers

Figure 4.3 presents box plots of normalized betweenness for each year from 2016 through 2020, as well as cumulatively across all years within the CUPID grant proposal network. Faculty with high betweenness may act as brokers within the network, possibly controlling the flow of resources and thereby holding significant influence within the network's topology (Borgatti *et al.*, 2022, p. 183; Mali *et al.*, 2012, p. 236).

The median betweenness remains relatively low for each year and across all years,



**Figure 4.3:** Box plots of normalized betweenness centrality for Boise State’s CUPID grant proposal network, displayed by individual year and cumulatively for all years. Betweenness measures each node’s role as a broker within the network, with higher values indicating greater influence over the network’s flow of resources and information. The plots highlight a consistent pattern of a small number of influential brokers against a backdrop of nodes with lower brokerage roles.

indicating that the majority of nodes do not frequently act as brokers in the network. The presence of outliers in each yearly distribution, although less extreme in 2020, suggests that a small number of nodes have an exceptionally high betweenness. These nodes may be acting as significant brokers within the network. The range of betweenness centrality, as indicated by the spread of the box plots, does not vary drastically year over year, which could suggest that the role of brokers within the network is relatively stable over time.

The distribution of betweenness centrality in the CUPID grant proposal network suggests that, while the majority of faculty members are not frequently positioned as intermediaries in the network, there exists a small subset of individuals who hold considerable broker roles. The outliers with high betweenness centrality in each

year—and especially in the aggregate—are indicative of faculty who are positioned in influential roles, potentially controlling collaboration pathways and resource flows. This phenomenon aligns with the concept of brokerage in social networks, where certain nodes accrue power and influence due to their strategic position within the network (Mali *et al.*, 2012, p. 236).

Furthermore, the consistent spread of betweenness centrality over the years may reflect established roles within the research community that persist over time. These brokers can have profound impacts on the dynamics of collaboration, innovation, and the dissemination of knowledge within the network.

### **Structural Cohesion**

The network metrics outlined in Table 4.2 provide insights into each year’s network characteristics as well as an aggregated view for the entire period from 2016 to 2020. The analysis begins with the year 2016, which shows the lowest mean betweenness centrality at 106.13 for the period, indicating fewer central figures acting as bridges within the network. In 2020, there’s a noticeable improvement in the network’s connectedness and clustering coefficient, suggesting an enhanced capacity for integration over time. The cumulative data over five years highlight a network characterized by strong connectedness, moderate clustering, and an average path length of around four steps, reflecting a network with diverse collaborative interactions.

For the year 2019, the network is distinct, characterized by a large number of actors (213 co-proposers) but the lowest mean degree (3.18) within the period. This suggests a large pool of participants with potentially underleveraged collaborative opportunities. Despite a high level of participation, the number of collaborative

**Table 4.2:** Fundamental network metrics of Boise State’s CUPID grant proposal network from 2016 to 2020, and cumulatively over the five-year period. The table showcases the evolving nature of the network’s mean degree, mean betweenness, connectedness, clustering coefficient, and average path length.

| Year | Mean Degree | Mean Betweenness | Connectedness | Clustering Coefficient | Average Path Length |
|------|-------------|------------------|---------------|------------------------|---------------------|
| 2016 | 3.236715    | 106.1256         | 0.2985320     | 0.4901099              | 4.380150            |
| 2017 | 3.333333    | 205.3897         | 0.4465852     | 0.4649299              | 5.282987            |
| 2018 | 3.794392    | 160.9299         | 0.4429380     | 0.4583508              | 4.365222            |
| 2019 | 3.183099    | 218.9718         | 0.3756754     | 0.5238402              | 6.418234            |
| 2020 | 4.260355    | 141.4556         | 0.5235982     | 0.5811785              | 4.168806            |
| 5yr  | 5.757847    | 467.6480         | 0.6886482     | 0.3207141              | 4.038870            |

proposals was 155, lower than the previous year, which had the most proposals. The mean betweenness centrality for 2019 stood at 218.97, highlighting the reliance on certain faculty members to connect different parts of the network, suggesting a disparity in collaborative influence and resources. The network’s connectedness score and the average path length for 2019 indicate a more segmented structure, with more indirect paths and less direct collaboration, complemented by a high clustering coefficient, which points to small, tightly-knit groups.

The density metrics, as shown in Table 4.3, shed light on the evolving connectivity within the grant proposal network from 2016 to 2020. The early years, 2016 and 2017, show a sparser pattern of connections, with a notable increase in network density by 2020, suggesting a gradual enhancement in interconnectivity among faculty members.

In 2020, the network underwent a transformation with a smaller size and fewer collaborative proposals compared to previous years, as detailed in Table 4.1. However, the mean degree increased to 4.26, indicating that the remaining faculty members

were more interlinked. This year also recorded the highest connectedness and clustering coefficient, pointing towards a more cohesive and tightly-knit network. These changes might reflect an adaptive shift towards more substantial cross-disciplinary collaborations, possibly in response to the challenges posed by the COVID-19 pandemic. A lower mean betweenness centrality suggests a reduced role of central brokers, potentially impacting the involvement of less established researchers. The observed increase in network density indicates a higher potential for collaboration among faculty members, while also hinting at the possible absence of newer researchers from the network.

**Table 4.3: Density Table of Historical Grant Proposal Networks.**

| Year | Edges | Dyads Possible | Density   |
|------|-------|----------------|-----------|
| 2016 | 335   | 21321          | 0.0157122 |
| 2017 | 355   | 22578          | 0.0157233 |
| 2018 | 406   | 22791          | 0.0178140 |
| 2019 | 339   | 22578          | 0.0150146 |
| 2020 | 360   | 14196          | 0.0253593 |
| 5yr  | 1284  | 99235          | 0.0129390 |

**Moving to the Discussion Section** While whole network metrics do well to describe the networks, the comparisons of the differences may not be significant. Scialbolazza *et al.* (2017) offers methodologies that accommodate longitudinal network comparison and clustering analysis required. They examine the evolution of research communities and interdisciplinary collaborations within a university setting over a period of three years (Scialbolazza *et al.*, 2017). They introduce a method that employs community-detection algorithms to identify consistent collaborative subgroups over

time and utilize ERGMs to explore the factors driving interdisciplinary collaborations (Sciabolazza *et al.*, 2017). By detecting clusters in yearly networks and identifying researchers who consistently participate in the same collaborative groups, this method filters out ephemeral collaborations, offering a robust framework for longitudinal network analysis. The analysis of subgroups and the overall network structure allows for examining shared attributes, offering insights into the collaborative dynamics in scientific communities (Borgatti *et al.*, 2022, p. 2-3,214). The approach to longitudinal analysis exemplified by Sciabolazza *et al.* (2017) holds considerable promise for dissecting the yearly dynamics within the grant proposal network. Nonetheless, given the constraints of this thesis, the statistical focus is directed toward an aggregated analysis spanning five years, aiming to capture an overarching view of the network's collaborative dynamics.

#### 4.4.2 Interpreting ERGM Dependence Model

ERGMs represent a sophisticated statistical framework designed for the analysis of network data, allowing for the modeling of complex network structures and the interactions between network actors, both through their endogenous relationships and exogenous attributes. This study employs ERGMs to dissect the intricate patterns and dependencies within our social network, aiming to unravel how individual attributes and the overall network configuration contribute to the formation of ties. Specifically, the selected ERGM analyzes a variety of dyadic independence and dependence constructs, such as college uniform homophily, proposal quartile differential homophily, and college sociality, alongside geometrically weighted degree (GWD) for k-stars and geometrically weighted edgewise shared partners (GWESP) for transitivity. The goal of utilizing an ERGM is to provide a nuanced understanding of the

underlying structural behaviors and broad patterns within the network, as evidenced by the results presented in several tables for comprehensive analysis and discussion.<sup>7</sup>

### Probability of A Tie

The edges term in the 5-year network ERGM (Table 4.5) output has an estimate of -10.48366 with a highly significant z-value of -29.921, indicating an extremely low p-value ( $< 1e - 04$ ). This term acts analogously to the intercept in logistic regression and is a crucial indicator of the network's overall propensity for tie formation (Harris, 2014, p. 52-53). In this context, the negative coefficient of the edges term suggests that the overall likelihood of tie presence between any two faculty in the network is lower than what would be expected if the ties were formed randomly. This significant negative edges term can imply that the grant proposal network has a significantly lower density compared to a random network. In other words, ties are not formed indiscriminately across the network; instead, they are likely influenced by specific factors or constraints that limit the number of ties each faculty member tends to form. Such constraints could be due to limited resources, time, or the strategic selection of collaboration partners based on shared research interests, funding opportunities, or existing collaborative relationships.

### Start Working Here:

“To predict the probability of a tie based on the dependence model, we now need to know not only the attributes of the two network members but also the degree for each person in the dyad and the number of edgewise shared partnerships. The change statistics for GWD and GWESP are substituted into the model along with

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<sup>7</sup>The complete summary of the final model selected for this study can be found in Appendix F.

coefficients and change statistics for the attributes” (Harris 2014 p. 86)

### Decay Parameter and the Change Statistic

The change statistic is the differences in statistics that result in changing  $x_{ij}^{(m-1)}$  to  $1 - x_{ij}^{(m-1)}$  given the rest (Lusher *et al.*, 2013, p.146). Change statistics are calculated using the decay parameter  $\alpha$ , which is 0.35 for both GW terms in the selected model.

GWD term is defined as

$$\delta_{GWD} = (1 - e^{-\alpha})^i + (1 - e^{-\alpha})^j, \quad (4.3)$$

where  $\alpha$  is a decay parameter set at 0.35 for the grant proposal network ERGM model, leading to a calculation of  $(1 - e^{-0.35})^i + (1 - e^{-0.35})^j = 0.2953 + 0.2953 = 0.5906$ .

The change statistic for GWESP, denoted as

$$\delta_{GWESP} = (1 - e^{-\alpha})^{ij_{ESP}}, \quad (4.4)$$

where  $\alpha$  is a decay parameter set at 0.35 for the grant proposal network ERGM model, leading to a calculation of  $1 - e^{-0.35} = 0.2953$ .

”An ERGM prescribes now likely it is to add or delete a tie for a pair of actors given everything else” (Lusher *et al.*, 2013, p. 55). The log-odds for the presence of a tie . . .

HARRIS: The change statistic is substituted into the model along with the coefficients and change statistics for the dyadic independent terms. Because the model has a large number of terms, only use terms t

This specific value indicates how the log odds of forming a tie between two nodes,  $i$ , and  $j$ , are influenced by the existing connections (Harris, 2014, p. 83-84).

**End Working HERE****Uniform Homophily Analysis**

The nodematch ERGM term for various colleges, as seen in Table 4.4, points to a strong presence of uniform homophily. Homophily refers to the propensity for individuals to establish connections with others who share similar attributes, in this context, belonging to the same academic college, as opposed to heterophily, which denotes tie formation among individuals with differing attributes. The positive coefficients across all college categories indicate a clear trend of homophily—faculty members are significantly more likely to collaborate on grant proposals with colleagues from their own college than with those from different colleges. This implies that discipline-centric or “short-distance” interdisciplinary collaborations are prevalent within the network.

For instance, the nodematch coefficient for the College of Arts & Sciences is 0.87990 with a p-value of less than 0.0001, suggesting a high likelihood of intra-college collaboration, a pattern that is statistically significant and robust. This is further quantified by an odds ratio of 2.4107, meaning faculty members in the College of Arts & Sciences are more than twice as likely to co-propose with each other compared to chance. The College of Business & Economics, exhibits the strongest homophily with an odds ratio of 8.0327, meaning that faculty in this college are more than eight times as likely to collaborate with each other than with faculty from other colleges, as evidenced by a high coefficient of 2.08352.

These findings indicate that researchers tend to favor collaboration with colleagues from their own college, suggesting a propensity for within-discipline or closely aligned interdisciplinary grant proposal partnerships. This could reflect comfort in shared

scholarly language, ease of communication, or possibly administrative and structural incentives within colleges that promote such shorter-distance collaborations. The lack of negative coefficients in the analysis suggests that long-distance interdisciplinary collaborations, while not absent, are less common than might be expected by chance, possibly pointing to barriers or a lack of incentives for cross-college interdisciplinary research endeavors, as identified in the qualitative analysis. This trend has implications for the structure of academic collaboration networks and could inform network interventions aiming to foster interdisciplinary research.

**Table 4.4**

| <b>Variable</b>                            | <b>Estimate</b> | <b>StdError</b> | <b>zvalue</b> | <b>pvalue</b> |
|--|-----------------|-----------------|---------------|---------------|
| edges                                      | -10.48366       | 0.35038         | -29.921       | < 1e-04       |
| nodematch College Arts & Sciences          | 0.87990         | 0.10537         | 8.350         | < 1e-04       |
| nodematch College Business & Economics     | 2.08352         | 0.23722         | 8.783         | < 1e-04       |
| nodematch College Education                | 1.57093         | 0.12385         | 12.684        | < 1e-04       |
| nodematch College Engineering              | 0.96073         | 0.10108         | 9.505         | < 1e-04       |
| nodematch College Health Sciences          | 2.03462         | 0.22102         | 9.206         | < 1e-04       |
| nodematch College Innovation and Design    | 1.84795         | 0.57158         | 3.233         | 0.001225      |
| nodematch College Other                    | 0.68457         | 0.17487         | 3.915         | < 1e-04       |
| nodematch College School of Public Service | 1.92168         | 0.21775         | 8.825         | < 1e-04       |

**Uniform Homophily Discussion** The analysis of the nodematch ERGM terms uncovers a pronounced trend towards uniform homophily, highlighting a strong inclination among faculty members to collaborate within their own colleges. This observed preference for shorter-distance interdisciplinary collaborations, as evidenced by sig-

nificant positive coefficients across all college categories (Table 4.4), aligns with the broader discourse on the nature of academic collaborations. While intradisciplinary work continues to be a cornerstone of knowledge production within specific domains, the push towards interdisciplinary research is increasingly recognized as crucial for addressing complex societal challenges (Huang *et al.*, 2023; Lyall *et al.*, 2013). This transition underscores the imperative for academic institutions to foster environments conducive to interdisciplinary engagement, as emphasized by LaRosa (2023b, personal communication, September 25) in the context of Boise State's strategic direction towards integrated research efforts.

However, the current state of collaboration, characterized by a marked preference for within-college partnerships, suggests potential barriers to the deep integration of disciplines advocated by funding bodies and institutional leadership. The significant homophily within the College of Business & Economics, for instance, indicates a robust internal collaboration network but also hints at missed opportunities for cross-disciplinary research that could emerge from genuine partnerships. The challenge, therefore, lies in bridging the gap between the existing practice of college-centric collaborations and the aspirational model of authentic, co-created interdisciplinary research that spans beyond superficial integration. This gap represents not only a methodological limitation but also a strategic one, as the success of interdisciplinary ventures is increasingly tied to their ability to synergize diverse disciplinary perspectives from the ground up. Addressing this challenge requires deliberate institutional strategies aimed at lowering the barriers to interdisciplinary research, enhancing the appeal of longer-distance interdisciplinary collaborations, and aligning with the evolving priorities of research funding landscapes.

### Differential Homophily Analysis

The nodemix term for the proposal count quartile attribute within the five-year grant proposal network elucidates patterns of both homophilous and heterophilous interactions among researchers, based on their co-proposal activity, segmented into quartiles—where quartile ranks are assigned from one (lowest proposal activity) to four (highest proposal activity), determining the propensity for collaboration among faculty with similar or varying levels of proposal engagement. Table 4.5 details the differential homophily ERGM results, where the reference category represents collaborations between researchers both within the first quartile of proposal activity. Within this context, ‘mix prop quartile 1.2’ denotes collaboration between a researcher in the first quartile and a researcher in the second quartile, indicative of heterophilous interaction. Conversely, a term such as ‘mix prop quartile 2.2’ symbolizes homophilous collaboration, where both collaborating researchers are within the second quartile. Similarly, ‘mix prop quartile 3.3’ and ‘mix prop quartile 4.4’ represent homophilous collaborations within the third and fourth quartiles, respectively, with higher estimates suggesting increased homophily among researchers with greater proposal activity.

**Mixing Proposal Activity** The statistical analysis of collaboration patterns within the five-year grant proposal network, as demonstrated by the ERGM results, uncovers significant patterns of collaboration across different levels of proposal activity, particularly between the first and fourth quartiles. Specifically, the ‘mix prop quartile 1.4’ estimate of 0.98916 ( $p < 0.001$ ) and the ‘mix prop quartile 2.4’ estimate of 1.86755 ( $p < 0.001$ ) reveal a statistically significant likelihood of collaboration between faculty with the lowest proposal activity (first and second quartiles) and those

with the highest (fourth quartile). This finding suggests scholars characterized by a lower volume of proposals are entering into collaborative endeavors with their counterparts who exhibit a higher frequency of proposal activity. Such interactions may be indicative of disparities across academic disciplines, each with its unique funding requirements, or may denote variations in proficiency and experience in the domain of grant proposal authorship, alongside other possible factors.

In more accessible terms, the higher the estimate and the lower the p-value, the stronger the evidence that researchers in lower activity quartiles are indeed collaborating with those in the highest quartile (Table 4.8). For instance, the odds ratio (OR) for ‘mix prop quartile 1.4’ is 2.6890, with a confidence interval ranging from 1.7432 to 4.1479, indicating that less active grant-proposing researchers are over two and a half times more likely to collaborate with highly active grant-proposing researchers compared to chance alone. The findings are even more pronounced for ‘mix prop quartile 2.4’, where the OR of 6.4724 suggests that second-quartile researchers are more than six times as likely to partner with fourth-quartile peers. The patterns observed underscores a dynamic of strategic collaboration within the academic network, reflecting a spectrum of proposal activity levels. Specifically, the increased likelihood of collaboration between faculty members across different quartiles of proposal activity may indicate a complex interplay of strategic choices, where researchers align based on shared interests, complementary skills, or mutual benefits in grant-seeking endeavors.

The lower end of the proposal count quartile interactions suggests a more nuanced aspect of network dynamics. The ‘mix prop quartile 1.2’ estimate of 0.52340 ( $p = 0.041745$ ) indicates a statistically significant but relatively modest tendency for

collaboration between researchers in the first and second quartiles. The corresponding odds ratio of 1.6878, with a confidence interval from 1.0197 to 2.7934, suggests that researchers in the lowest quartile are somewhat more likely to collaborate with those just above them in the second quartile compared to chance alone.

Given that the reference category is 1.1 (homophilous collaboration within the first quartile), the relatively lower estimate and odds ratio for 1.2 suggests that while there is a tendency for those in the lowest quartile to co-propose with the second quartile, it's not as strong as the homophilous ties within the first quartile itself. This pattern may reflect a multifaceted approach to academic partnerships, where factors such as disciplinary funding needs, strategic alignment for resource sharing, or complementary research interests play a role. While mentorship or seeking collaborative opportunities could be motivations, they are part of a broader spectrum of considerations driving collaborations across different levels of proposal activity.

**Cumulative Advantage** The ERGM results for the five-year grant proposal network point to a clear pattern of cumulative advantage, aligning with the notion of preferential attachment within the upper echelons of academic activity. The ‘mix prop quartile 3.3’ with an estimate of 2.04987 ( $p < 0.001$ ), ‘mix prop quartile 3.4’ with an estimate of 2.29764 ( $p < 0.001$ ), and ‘mix prop quartile 4.4’ with an estimate of 2.54906 ( $p < 0.001$ ), all signify a statistically significant and strong tendency of collaboration within and between the third and fourth quartiles. These quartiles represent well-established researchers, suggesting that such individuals are more likely to collaborate with peers who share a similarly high level of research activity and recognition within the scientific community, as per the framework described by Mali *et al.* (2012, p. 218, 232).

In plain language, the statistics indicate that researchers who are highly active in submitting proposals are not only more likely to work with each other, but this tendency strengthens as the level of activity and recognition increases. The odds ratios underscore the intensity of this pattern: researchers in the third quartile are approximately 7.77 times more likely to collaborate among themselves (3.3), and nearly 10 times more likely to partner with those in the fourth quartile (3.4). The trend peaks within the fourth quartile (4.4), where researchers are 12.8 times more likely to collaborate with one another compared to random chance. These findings suggest that a “rich getting richer” effect is at play, where already successful academics continue to build their network predominantly with those of similar or higher status, potentially creating an insular elite within the scientific community that may have implications for the distribution of resources and opportunities.

**Differential Homophily Discussion** The ERGM analysis offers robust empirical support for the notion of preferential attachment within the grant proposal network, particularly evident in the strong propensity of high-quartile researchers to collaborate amongst themselves. This trend encapsulates a network dynamic that mirrors the cumulative advantage theory, where the accrual of resources and recognition is skewed towards those who have already attained success, likely reinforcing a cycle of a homophilic preferential attachment and the consolidation of a distinct subgroup within the upper quartiles (Mali *et al.* (2012); Newman (2001)). Such a scenario aligns with the principles of preferential attachment and differential homophily described by Goodreau *et al.* (2009), and is reflected in the specialized interaction patterns identified by Lane *et al.* (2020) in academic settings.

In contrast, the interaction patterns between lower and higher quartiles reveal

**Table 4.5:** Estimated coefficients for nodemix effects by proposal count quartile in the ERGM analysis of the five-year grant proposal network. The interaction effects between nodes of differing proposal activity quartiles, with a focus on homophilous and heterophilous ties. The first quartile (quartile 1 with quartile 1) serves as the reference category for comparisons.

| Variable              | Estimate  | StdError | zvalue  | pvalue   |
|-----------------------|-----------|----------|---------|----------|
| edges                 | -10.48366 | 0.35038  | -29.921 | < 1e-04  |
| mix prop quartile 1.2 | 0.52340   | 0.25707  | 2.036   | 0.041745 |
| mix prop quartile 2.2 | 1.31860   | 0.38993  | 3.382   | 0.000721 |
| mix prop quartile 1.3 | 0.72794   | 0.23769  | 3.062   | 0.002195 |
| mix prop quartile 2.3 | 1.85877   | 0.30258  | 6.143   | < 1e-04  |
| mix prop quartile 3.3 | 2.04987   | 0.30113  | 6.807   | < 1e-04  |
| mix prop quartile 1.4 | 0.98916   | 0.22114  | 4.473   | < 1e-04  |
| mix prop quartile 2.4 | 1.86755   | 0.29141  | 6.409   | < 1e-04  |
| mix prop quartile 3.4 | 2.29764   | 0.28886  | 7.954   | < 1e-04  |
| mix prop quartile 4.4 | 2.54906   | 0.28873  | 8.829   | < 1e-04  |

a potential mentorship mechanism, suggesting that less established researchers seek collaborations with established scholars. The disparity between the valuation and the pursuit of mentorship, as pointed out by Norton *et al.* (2017), indicates that while mentorship is esteemed for fostering collaboration, it is less frequently an impetus among star scientists. This disconnect presents a compelling case for institutional policies to foster a mentorship culture that could help mitigate the hierarchical distribution of expertise and promote a more balanced collaboration landscape.

## Sociality Analysis

The nodefactor ERGM term sheds light on the varying propensities of faculty members from any one college to engage in collaborative grant proposals, with the College of Arts and Sciences serving as the reference category (Table 4.6). This term, essentially measuring the "sociality" of each college, reveals that certain colleges are more active in seeking out grant proposal collaborations than others, with the College of Arts and Sciences serving as the reference point for comparison.

Faculty from the College of Innovation and Design and the colleges in the category 'Other' show a significantly higher likelihood of participating in grant proposals compared to their counterparts in the College of Arts and Sciences. Specifically, the College of Innovation and Design exhibits a notable increase in collaborative propensity, with an estimate of 0.34428 ( $p = 0.002645$ ) and an odds ratio of 1.4110, indicating that faculty in this college are about 41% more likely to co-propose than those in the College of Arts and Sciences. Similarly, the miscellaneous 'Other' colleges show a strong inclination towards collaboration, with an estimate of 0.33685 ( $p < 0.0001$ ) and an odds ratio of 1.4005, suggesting a 40% higher likelihood of co-proposing.

Conversely, faculties from the College of Education, College of Engineering, and College of Health Sciences exhibit a slight decrease in collaborative tendencies, as indicated by negative estimates, though these are not statistically significant. This suggests that, compared to the College of Arts and Sciences, these colleges are less inclined towards grant proposal collaboration, but the difference is not large enough to be conclusive.

The reference category plays a crucial role in this interpretation, as it sets the baseline for comparison. Since the College of Arts and Sciences is used as the benchmark,

a positive coefficient for another college indicates a higher propensity for collaboration relative to this reference. Conversely, a negative coefficient, though not significantly different in this analysis, would suggest a lower propensity compared to the College of Arts and Sciences. This analysis highlights the diverse collaborative dynamics across different academic units, with certain colleges exhibiting a more pronounced inclination towards grant proposal collaborations, potentially reflecting varying cultural or structural incentives within these units for collaborative research activities.

**Table 4.6**

| Variable                                    | Estimate  | StdError | zvalue  | pvalue   |
|---|-----------|----------|---------|----------|
| edges                                       | -10.48366 | 0.35038  | -29.921 | < 1e-04  |
| nodefactor College Business & Economics     | 0.10104   | 0.12144  | 0.832   | 0.405432 |
| nodefactor College Education                | -0.07747  | 0.07522  | -1.030  | 0.303026 |
| nodefactor College Engineering              | -0.02210  | 0.07671  | -0.288  | 0.773260 |
| nodefactor College Health Sciences          | -0.18579  | 0.13340  | -1.393  | 0.163718 |
| nodefactor College Innovation and Design    | 0.34428   | 0.11452  | 3.006   | 0.002645 |
| nodefactor College Other                    | 0.33685   | 0.07442  | 4.526   | < 1e-04  |
| nodefactor College School of Public Service | 0.05614   | 0.11376  | 0.494   | 0.621637 |

**Sociality Discussion** The sociality of each college within the grant proposal network at Boise State, as indicated by the nodefactor ERGM term, underscores the variable propensity of colleges to engage in collaborative grant proposals. With the College of Arts and Sciences serving as a reference point, it becomes evident that researchers in certain colleges, notably the College of Innovation and Design and the 'Other' category, exhibit a markedly higher inclination towards collaboration in grant

applications. This finding aligns with the broader understanding of collaboration's pivotal role in enhancing scientific discovery and innovation (Sonnenwald, 2007; Disis & Slattery, 2010). Such collaboration, as evidenced by the propensity to co-propose, reflects the essential social process of scientific endeavor, contributing to a richer knowledge base, extended networks, and the dynamic, connective thinking that fuels radical innovations (Disis & Slattery, 2010).

The differential collaborative propensities observed across colleges do not represent intra- or interdisciplinary efforts but underscore the inherent sociality within academic units, highlighting how certain colleges might be more actively seeking opportunities for collaborative grant proposals. This pursuit of collaboration is crucial for addressing the complex challenges that transcend the autonomy benefits of working alone. The findings from this analysis contribute to a nuanced understanding of how historical collaborative dynamics align with the university's strategic goals, emphasizing the importance of fostering a thriving community through enhanced research quality and scientific credibility (Boise State University, 2024). Moreover, the diverse expertise and mentoring inherent in collaborative efforts, as indicated by the significant positive coefficients for some colleges, resonate with the literature suggesting that collaborative outputs often surpass the quality of single-authored works due to more rigorous scrutiny and intellectual exchange (Hart, 2000). Thus, the sociality of colleges, as determined by their propensity to co-propose, not only reflects their active engagement in the scientific community but also underscores the strategic importance of fostering collaborative environments to enhance the overall quality and impact of research at Boise State.

## Alternating Stars

GWD recovers degree popularity. Table 4.7 displays the GWESP and GWD ERGM results. The GWD has a positive significance (3.86187;  $p < 1e-04$ ). Grant proposers with a high degree are more prevalent in the network than would be expected by chance would suggest (Harris, 2014, p. 85). The log-odds for the GWD term, with a lower bound of 25.8321, an odds ratio (OR) of 47.5544, and an upper bound of 87.5430, supported by a Wald statistic of 12.4034, illuminate the strength and significance of this relationship within the network. Additionally, Harris (2014, p. 85) elucidates that the log-odds of forming a tie are highest when nodes have zero degrees, indicating an "antipreferential attachment" mechanism where newer nodes are just as likely, if not more, to form ties, challenging the notion that only well-connected nodes gain more connections.

The positive estimates signify edge dispersion across the network (Levy, 2016), suggesting a more equitable distribution of ties, where connections are spread out rather than centralized around specific "scientific stars." This dispersion, supported by the log-odds results, indicates a network characterized by a greater number of highly connected nodes, aligning with the network's tendency towards inclusivity in collaboration and indicating a diverse collaboration pattern (Harris, 2014, p. 83). The implications of the log-odds findings, emphasizing the diminishing increase in tie formation likelihood as node degree grows, further complicate the interpretation of GWD's positive value, necessitating careful consideration of network dynamics beyond mere sign and magnitude.

Discussion (limitation): The GWD interpretation, while indicative of dispersion, lacks a baseline or threshold against which to gauge the degree of dispersion or cen-

tralization effectively. The positive value underscores a tendency towards dispersed connections, yet without additional context or comparative metrics, it's challenging to ascertain the extent of dispersion or its significance within the network's overall structure. This scenario underscores the need for caution in drawing conclusions about network dynamics solely based on the sign and magnitude of GWD estimates without comparative analysis or benchmarks.

**Table 4.7**

| Variable         | Estimate  | StdError | zvalue  | pvalue  |
|------------------|-----------|----------|---------|---------|
| edges            | -10.48366 | 0.35038  | -29.921 | < 1e-04 |
| gwdeg fixed 0.35 | 3.86187   | 0.31135  | 12.403  | < 1e-04 |
| gwesp fixed 0.35 | 3.28750   | 0.10425  | 31.535  | < 1e-04 |

## Transitivity

The GWESP term exclusively addresses the distribution of shared partners among connected researchers, particularly how shared co-proposal partners influence the formation of new collaborative ties. With all else held constant, the positive and significant GWESP coefficient 3.28750 ( $p < 1e - 04$ ) implies that the formation of additional ties for each dyad is more probable than by chance (Harris, 2014, p. 85).<sup>8</sup> This is evidenced by an odds ratio of 26.7759, within a confidence interval ranging from 21.8276 to 32.8461, and supported by a Wald statistic of 12.4034, highlighting a

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<sup>8</sup>The addition of a tie in the network affects the number of Edgewise Shared Partners (ESP) not just for the two nodes directly involved in the new tie but also for other nodes throughout the network (Harris, 2014, p. 83). The distribution of the observed grant proposal network's ESP distribution shows that many nodes have fewer connections in a histogram of ESP.

network's inclination towards forming collaborative clusters or triangles. This implies that the presence of shared collaborators between two faculty members significantly increases the likelihood of them co-proposing a grant, aligning with the concept that mutual connections can foster new collaborations due to perceived social value or affinity (Goodreau *et al.*, 2009; Lusher *et al.*, 2013).

**Discussion** The GWESP results signify a network where faculty members are substantially more inclined to co-propose with others who share mutual collaborators, reflecting a community that values established connections and potentially operates within well-defined disciplinary or thematic triangles. This finding resonates with Harris 's 2014 explanation that the log-odds of tie formation between any two nodes increase significantly when they share common partners, especially when these nodes have fewer direct connections ((Harris, 2014, p. 83-84)). The significant GWESP term underscores the importance of social cohesion in the grant proposal process, suggesting that the network's structure is conducive to collaboration and knowledge exchange within established triangles.

(Table 4.8)

#### **4.4.3 Conclusion**

##### **WORKING HERE**

**Table 4.8**

| Odds Ratios and Wald Test Statistics        |         |         |         |          |
|---|---------|---------|---------|----------|
| Term  | Lower   | OR      | Upper   | Wald     |
| edges                                       | 0.0000  | 0.0000  | 0.0001  | -29.9211 |
| mix.prop_quartile.1.2                       | 1.0197  | 1.6878  | 2.7934  | 2.0361   |
| mix.prop_quartile.2.2                       | 1.7408  | 3.7382  | 8.0274  | 3.3816   |
| mix.prop_quartile.1.3                       | 1.2996  | 2.0708  | 3.2996  | 3.0625   |
| mix.prop_quartile.2.3                       | 3.5456  | 6.4158  | 11.6094 | 6.1431   |
| mix.prop_quartile.3.3                       | 4.3044  | 7.7669  | 14.0144 | 6.8072   |
| mix.prop_quartile.1.4                       | 1.7432  | 2.6890  | 4.1479  | 4.4729   |
| mix.prop_quartile.2.4                       | 3.6561  | 6.4724  | 11.4582 | 6.4087   |
| mix.prop_quartile.3.4                       | 5.6490  | 9.9507  | 17.5281 | 7.9542   |
| mix.prop_quartile.4.4                       | 7.2656  | 12.7950 | 22.5326 | 8.8286   |
| nodefactor.College.Business_&_Economics     | 0.8720  | 1.1063  | 1.4036  | 0.8320   |
| nodefactor.College.Education                | 0.7986  | 0.9255  | 1.0725  | -1.0300  |
| nodefactor.College.Engineering              | 0.8416  | 0.9781  | 1.1368  | -0.2881  |
| nodefactor.College.Health_Sciences          | 0.6394  | 0.8304  | 1.0786  | -1.3927  |
| nodefactor.College.Innovation_and_Design    | 1.1273  | 1.4110  | 1.7660  | 3.0063   |
| nodefactor.College.Other                    | 1.2104  | 1.4005  | 1.6205  | 4.5264   |
| nodefactor.College.School_of_Public_Service | 0.8463  | 1.0577  | 1.3220  | 0.4935   |
| nodematch.College.Arts_&_Sciences           | 1.9608  | 2.4107  | 2.9637  | 8.3502   |
| nodematch.College.Business_&_Economics      | 5.0458  | 8.0327  | 12.7877 | 8.7829   |
| nodematch.College.Education                 | 3.7742  | 4.8111  | 6.1330  | 12.6838  |
| nodematch.College.Engineering               | 2.1439  | 2.6136  | 3.1863  | 9.5046   |
| nodematch.College.Health_Sciences           | 4.9601  | 7.6494  | 11.7966 | 9.2058   |
| nodematch.College.Innovation_and_Design     | 2.0702  | 6.3468  | 19.4578 | 3.2331   |
| nodematch.College.Other                     | 1.4075  | 1.9829  | 2.7935  | 3.9147   |
| nodematch.College.School_of_Public_Service  | 4.4588  | 6.8324  | 10.4696 | 8.8251   |
| gwdeg.fixed.0.35                            | 25.8321 | 47.5544 | 87.5430 | 12.4034  |
| gwesp.fixed.0.35                            | 21.8276 | 26.7759 | 32.8461 | 31.5351  |

## CHAPTER 5:

## LOVE

### 5.1 Charting the Evolution of Research

#### Collaboration

Initiating network interventions at Boise State signals a new era of creative work. This chapter outlines the dawn of advanced collaborative practices at Boise State, charting the potential within its research teams prior to the infusion of network treatments. The SNAP initiative, particularly its LOVE branch, seeks to assess the impact of the GCs' investments and whether they foster exemplary teams and create broader opportunities within the university's academic landscape. In this thesis, a path is mapped for subsequent analysis of how such treatments influence scientific collaboration, productivity, and the expansion of interdisciplinary opportunities across campus and transdisciplinary opportunities across local, regional, and national interests.

The potential of network interventions, as defined by Valente (2012), moves to enhance organizational performance and facilitate behavior change by intentionally altering network connections. With SNA as a tool, this study aims to propose methods for modifying existing network structures to promote interdisciplinary collaboration. Such interventions are designed to address the biases in collaboration patterns and connect disparate scientific communities (Valente, 2012; Vacca *et al.*, 2015), bolstering

team resilience and diversity within research networks.

Concerns exist about the distribution of resources and opportunities, with programs potentially favoring established faculty (LaRosa, 2023b, personal communication, September 25; Disis & Slattery, 2010; Sonnenwald, 2007), underscores the need for strategic efforts. These efforts ensure the investments align with Boise State's goals to expand a culture of innovation, build scalable structures, and create a collective opportunity with a whole institutional impact (Boise State University, 2024) to ensure that GCs' investments do not inadvertently reinforce existing disparities. These goals can be achieved by constructing new connections and expanding networks for the thematic areas identified by interdisciplinary teams.

Interdisciplinary teaming conflicts not only cripple scientific productivity but also risk the very investments meant to spur innovation, highlighting the urgency of navigating these challenges effectively. These concerns—crossing disciplinary boundaries, scarcity of time, institutional structures, interpersonal relationships, leadership, and expanding opportunities for equality—form the backbone of this analysis on fostering effective team science networks. Addressing these concerns is pivotal, especially those that span different disciplines and include community stakeholders, are recognized for producing the most impactful work and groundbreaking innovations (Sonnenwald, 2007; Disis & Slattery, 2010; Hart, 2000; Enns *et al.*, 2023; Lieberknecht *et al.*, 2023).

Love *et al.* (2021) research highlights a gap in the literature on the underexplored effectiveness of support strategies, such as training and performance metrics, in enhancing the productivity and expertise of interdisciplinary scientific teams. Love *et al.* (2021) reveal a significant correlation between mentoring, advice networks, and scientific productivity, indicating that specific support strategies can profoundly impact

team success.

The Love *et al.* (2021) study unveils a significant correlation between mentoring, advice networks, and scientific productivity. It illustrates how being part of a team bolsters members' skills, relationships, and professional growth, thus fueling their scientific achievements. This research underscores the transformative power of social dynamics in the knowledge-creation process, with interpersonal relationships at the core of team success (Love *et al.*, 2021). Such insights highlight the shift from individual achievements to collective progress, emphasizing the critical role of nurturing interpersonal relationships within teams. The SNAP project leverages these findings in initiating a rigorous empirical investigation.

This effort aims to assess how intensive research collaborations within the GCs initiative evolve and impact the nature of collaborative relationships over time. By replicating the mid-point survey by Love *et al.* (2021), this thesis seeks to establish a baseline of collaborative relationships at Boise State. The research not only addresses immediate inquiries about interdisciplinary teamwork but also prepares the ground for a detailed examination of how networks transform. Moreover, this methodology seeks to enrich our comprehension of team dynamics, providing insights that benefit both Boise State and the wider academic community, highlighting the effectiveness of targeted interventions in achieving success across a spectrum of interdisciplinary teams.

Building on the foundational insights explored in this introductory section, the subsequent parts of this chapter will delve deeper into the practical application and empirical study of network treatments within Boise State's research ecosystem. This study details the case study teams, emphasizing the range of network treatments they

receive—from comprehensive resources and training to limited or no interventions. It then establishes the criteria for an exemplary team, concentrating on scientific productivity, team resilience, and the capacity to nurture interdisciplinary collaboration that expands academic opportunities across the campus. These criteria guide the analysis of survey data in the subsequent section, focusing on team members' characteristics and the complex networks they form. By comparison of these networks, the study outlines a framework for analyzing the impact of network treatments on fostering productive, resilient, and convergently transdisciplinary research teams. Such analysis sets the foundation for a comprehensive discussion on the potential for institutional collaborative advancement in the following chapter.

## 5.2 Method: SNA

This study draws its primary data from a pre-survey conducted using Qualtrics (Qualtrics, 2005), leveraging the survey framework established by Love *et al.* (2021). SNAP adapted Love's mid-point survey to design a pre-network treatment survey tailored to this research context. Those surveyed are members from the Grand Challenges initiative, classified into 2 Leadership, 4 Award, and 5 IRA teams, totaling 68 individuals. For confidentiality, respondents received unique IDs, and teams were assigned letters A to K. Non-response from 5 individuals led to one team being too small for analysis, thus, the survey analysis is based on 63 responses across 10 teams. The survey's outcomes are systematically transformed into network objects, utilizing the 'network' (Butts *et al.*, 2023) and 'igraph' (Csárdi *et al.*, 2024) packages in R for comprehensive network analysis. This methodological approach enables the construction of directed graphs, essential for visualizing and analyzing the complex interactions within the research teams.

The analysis hinges on creating directed graphs crafted from survey responses where participants identified their connections to peers within the team. Such connections, or nominations, form the basis of the directed edges in the graphs, indicating the direction of the relationship from the nominator to the nominee. This method highlights the directionality of relationships, which is crucial for understanding the flow of influence and information among team members, aligning with the techniques suggested by Borgatti *et al.* (2022, p. 16). Further, the analysis considers both indegree—the count of incoming connections to a node—and outdegree—the count of outgoing connections, enriching the understanding of each team member's role within the network (Borgatti *et al.*, 2022, p. 184).

The concept of eigenvector centrality is also employed, which not only considers the direct connections a node has but also the centrality of those nodes to which it is connected, suggesting that links to highly connected nodes significantly boost a node's centrality score (Borgatti *et al.*, 2022, p. 172-174, 184). This nuanced measure of centrality helps reveal the network's influential researchers based on the premise that not all connections have equal value.

Additionally, the networks in this study are constructed with weighted ties, where the weights might be derived from Likert scale responses or from aggregating multiple types of ties. Given that aggregating data can introduce analytical complexities (Atkisson *et al.*, 2020; Borgatti *et al.*, 2022, p. 44; Domenico *et al.*, 2015; Górska *et al.*, 2017), careful consideration is given to assessing potential distortions this might cause. Through a systematic analysis of the multivariate networks, this study aims to comprehend the intricacies of team dynamics, thus enabling a more profound comprehension of how network interventions could potentially reshape these research

communities. By dissecting the layers of multivariate networks, the research strives to capture the depth of team interactions, which informs a deeper understanding of how network interventions might reshape these research communities. The section, “Outcome Measures,” delves into how these weighted, directed networks are instrumental in dissecting the structural nuances of team dynamics.

### 5.2.1 Networks

#### Understanding How Network

In this study, teams with a clear understanding of how each individual’s expertise aligns with the team’s objectives are more likely to achieve *scientific productivity* in the upcoming year. To explore this aspect, SNAP adapted a question from Love *et al.* (2021) to gauge team members’ perceptions of their colleagues’ contributions. Specifically, the survey asked: “Please indicate your level of understanding of how each individual’s expertise will contribute to the team,” providing responses ranging from “This is my name” to “Strongly Disagree.”

Assigning weights to these responses is a method I use to quantify the collective understanding within the team: ‘Strongly Agree’ indicates a high level of perceived contribution (weight = 3), ‘Agree’ shows agreement but to a lesser extent (weight = 2), ‘Neutral’ indicates ambiguity or a baseline understanding (weight = 1), while ‘Disagree’ or ‘Strongly Disagree’ suggest a perceived disconnect or lack of contribution, thus not forming a tie (weight = 0). The weightage system’s transformation of subjective insights into objective quantitative data enables an in-depth analysis of team dynamics, coherence, and the valuation of each member’s expertise within the team framework. These weighted responses then serve as the basis for evaluating the strength of social relationships within the team, which is crucial for assessing the

team's potential for future productivity.

### **Knowledge Of**

To assess the depth of knowledge team members possess regarding each other's scientific expertise, this study employs a nuanced approach inspired by Love *et al.* (2021). Participants were prompted to evaluate their understanding of each colleague's expertise, with response options designed to capture a gradient of familiarity—from a precise grasp of a colleague's specific area of expertise to a complete lack of knowledge. These responses, ranging from "I can describe their specific area of expertise very accurately" (assigned a weight of 3) to "I cannot describe their area of expertise at all" (assigned a weight of 0), were then quantified to serve as weighted edges within our network. This quantification process transforms subjective perceptions of expertise into measurable data points, enabling a structured analysis of knowledge depth within the team. Such a weighted approach not only illuminates the varying levels of understanding among team members but also lays the groundwork for evaluating the potential for interdisciplinary collaboration and synergy. By systematically quantifying these interactions, the study more accurately gauges the readiness of the team to engage in *convergent* collaborations that demand a comprehensive mutual understanding of diverse scientific backgrounds.

### **Professional and Personal Networks**

To understand the dynamics of team interactions, this study draws upon the methodology of Love *et al.* (2021), who explored how team members engage with one another across various contexts. Participants in this survey were asked to detail their inter-

actions with fellow team members through a comprehensive list of options, ranging from collaborative efforts like joint publications and grant proposals to more personal connections such as seeking advice or friendship. Notably, the SNAP project adjusted Love's original questionnaire by excluding the option for "NEW consulting or tech support projects" and delineating "joint publications" from "presentations or conference proceedings" to capture these interactions with greater specificity.

From these responses, individual networks were constructed for each type of interaction, with a directed edge representing each chosen relationship. These edges were assigned a weight of one to signify the presence of an interaction, facilitating the *aggregation* of edges into two multilayer networks: a "Professional" network comprised of scholarly and work-related interactions and a "Personal" network reflecting social and advisory relationships. The Professional network comprises the following networks: Joint Publications, Conferences, Grant Proposals, University Business, Committees, My Mentor, Their Mentor, and Professional Advice. The Personal network comprises Personal Advice, Hang Out, and Personal Friend networks. This dual-network framework offers a rich dataset for exploring the dynamics of team interactions.

### 5.2.2 Multilayered Networks

A multiplex (multilayered or multivariate) network is a social network formed by layers of different types of interactions (Atkisson *et al.*, 2020, p. 1), such as the Professional and Personal networks described above. Exploring Professional and Personal networks opens a pathway to understanding the layered dimensions of interactions that shape the collaborative climate and foster a cohesive research environment. The motivation to compare single-edge type networks is twofold. To address redundancy in multiplex networks (Domenico *et al.*, 2015) and ensure a comprehensive understand-

ing of social systems (Atkisson *et al.*, 2020), aggregation techniques are employed, allowing for a nuanced analysis that maintains the integrity of social connections across the network's entire framework.

Aggregation reduces the number of layers while maintaining maximum information about the social system (Domenico *et al.*, 2015). One layer can attribute social connections across the entire multiplex framework (Atkisson *et al.*, 2020). However, Atkisson *et al.* (2020) argue that the multiplexity of networks necessitates a holistic examination to circumvent skewed interpretations that might arise. “Weakly coupled layers behave like separate networks” (Górski *et al.*, 2017, p. 2). Networks with similar edges can be aggregated, whereas dissimilar-edged networks should not (Domenico *et al.*, 2015). It is also poor practice to aggregate disconnected or bridged cliques, as noted by Domenico *et al.* (2015, Supplimantary Table 1) such as creating a single network from all the GCs teams.

Another reason for comparing layers is that evaluating multilayered networks can reveal that specific layers are more important and influential in the multilayered network than others (Górski *et al.*, 2017). Comparing networks can elude to the multifaceted nature of social structures (Atkisson *et al.*, 2020).

Several approaches to exploring multilayered networks include the Quadratic Assignment Procedure (QAP), Exponential Random Graph Models (ERGMs), and a Von Neumann entropy modeling strategy.

Researchers often turn to QAP to identify correlations between network layers, particularly when comparing two matrices (networks) while adjusting for a third. This approach becomes more complex with each additional matrix due to the dependence, similar to multicollinearity in multiple regression (van Duijn & Huisman,

2011, p. 464). Relationships span various forms in professional environments, such as collaborations and social support, making them multidimensional (Lusher *et al.*, 2013, p. 213). Different relational ties, like friendship and advice, are interdependent and can influence one another (Lusher *et al.*, 2013, p. 214).

Chapter 4 introduced ERGMs as a method to address the interdependence within networks. ERGMs can also help uncover how various networks interact and impact the multilayer network's structure (Lusher *et al.*, 2013, p. 115-117). However, longitudinal data is necessary to decide whether one type of tie is likely to lead to another (Lusher *et al.*, 2013, p. 117). An extension to the ‘ergm’ package allows for the analysis of multilayered networks (Krivitsky, 2023).

However, the small size of team rosters renders multilayered ERGMs unsuitable for analysis at this stage. A third method for comparing multilayered networks boils out of the movement of physicists into SNA, bringing with them new modeling strategies (Mali *et al.*, 2012, p. 218). Domenico *et al.* (2015) detail a method for reducing networks while maximizing distinguishability using Jensen-Shannon distance (JSD) and Von Neumann (entanglement) entropy. An edge in a graph, similar to a pure state in quantum mechanics, exhibits zero Von Neumann entropy (Domenico *et al.*, 2015, p. 2). Higher Von Neumann entropy values in multilayered networks indicate more extensive divergence from a pure state (Domenico *et al.*, 2015, p. 2). Domenico *et al.* (2015) employ a stepwise aggregation process, selecting networks with the lowest JSD to observe changes in relative entropy from no to complete aggregation. While Domenico *et al.* use this method to determine whether an aggregation maximizes distinguishability, this method also illuminates information about the social structure. It is a valuable method for describing and comparing the networks.

Insights into these aggregations and their interrelations may reveal the underlying structure and the social processes that shape interactions. Thus, a tie in one network can predict a tie in another network. This thesis predicts that specific Professional networks will exhibit significant coupling: namely, the Grant Proposals with Joint Publications, University Business with Committees and Conferences networks, as well as My Mentor with Professional Advice networks. This hypothesis is grounded in the logical progression from obtaining research funding (Grant Proposals) to the scholarly dissemination of research outcomes (Joint Publications), suggesting a natural linkage between these activities. Similarly, University Business, Committees, and Conferences are anticipated to be intertwined, reflecting the interconnected nature of administrative and academic duties within university settings. The My Mentor and Professional Advice networks are expected to be coupled due to the mentorship relationship inherently involving the provision of professional guidance.

Conversely, a lack of coupling between My Mentor and Their Mentor networks is predicated on the expectation of concordance—defined by Ready & Power (2021) as the consistency in relationship reporting within a network. Such concordance implies that mentorship nominations should be reciprocal, with each party acknowledging the other's mentorship role, indicating that these networks will not be directly coupled due to the expectation of mutual recognition within the mentor-mentee dynamic.

This study's exploration of multiple and multilayer networks sheds light on the complex relationships of the GCs teams. The forthcoming section will delve into the profiles of survey participants, whose experiences and interactions within these networks will crucially inform our understanding of the initiative's impact on fostering a vibrant research community.

## 5.3 Methods: Case Study Teams

The survey participants are members of small GCs teams, which are categorized into three team types: Leadership, Award, and IRA. Team formation began with the two leadership teams coming together to promote the Grand Challenges. The awards devised by the leadership team created the award teams. Award teams received funds j\$100,000 to conduct a Grand Challenges topic pilot study but did not receive additional professional development network treatments. Five Interdisciplinary Research Advancement (IRA) teams, each with a unique thematic drive, received a small amount of money (\$25,000) to build their research network. Additionally, they are receiving the Interdisciplinary Research Accelerator (IRA) network treatment.

### 5.3.1 GCs Leadership Teams

Once funding was determined to promote the GCs, half a million per GC, CRCA needed to determine how to engage faculty (LaRosa, 2023b, personal communication, September 25). Two teams were conceptualized to invigorate faculty involvement in Grand Challenges. These leadership teams emerge as distinct entities, each marked by its unique approach and ethos.

#### Resource Nexus Leadership

With a budget of \$75,000 and a timeline from May 2022 to June 2023 for Phase 1, the Resource Nexus Leadership team aims to catalyze a transdisciplinary ecosystem at Boise State focused on sustainability and resilience (Brand, 2022). Their comprehensive approach includes establishing a shared leadership model, conducting asset mapping and a SWOT analysis to integrate and streamline university efforts, forming

an advisory committee to leverage diverse expertise, and engaging community and academic stakeholders to build a supportive network (Brand, 2022). They plan to document and promote their efforts through multimedia storytelling and a written record, develop a model to address common barriers to transdisciplinary work, and lay the groundwork for Phase II funding distribution (Brand, 2022). This strategic plan fosters collaborative research and creative activity, ultimately leading to more resilient urban and rural systems through the Resources Nexus for Sustainability GC.

The Resource Nexus Leadership team was self-assembled and driven by a shared vision. This team portrays passionate commitment and close-knit social bonds (LaRosa, 2023b, personal communication, September 25). This passion translated into tangible outcomes, with the team's collective effort resulting in three awards totaling \$400,000—a remarkable feat that underscores their dedication and synergy.

### **Healthy Idaho Leadership**

Contrasting sharply with the first, the second Leadership team was born out of administrative nomination. Comprising individuals appointed by Deans, this team's genesis was rooted in their employment responsibilities rather than a self-driven initiative.

LaRosa describes their approach as expedient and pragmatic, a demeanor that, while effectively accomplishing tasks, lacked the emotive drive of their counterparts (LaRosa, 2023b, personal communication, September 25). "They got the job done quickly," LaRosa notes, alluding to their efficient, albeit dispassionate, method of operation (LaRosa, 2023b, personal communication, September 25). This efficiency bore fruit in two substantial awards, each worth \$200,000, demonstrating their ability to deliver results calculatedly. However, the sustainability of such a team is inextricably

linked to the continuity of funding. Without a regular influx of financial resources, the future of this team hangs in a delicate balance (LaRosa, 2023b, personal communication, September 25). Their existence, shaped and sustained by administrative directives and funding streams, may need these elements to avoid dissolution.

The dichotomy between these two Leadership teams at Boise State University—one fueled by intrinsic motivation and social cohesion, the other by institutional mandate and functional expediency—offers a fascinating glimpse into the varied landscapes of academic collaboration. It underscores how different modes of team formation and the nature of their objectives can shape their immediate outcomes and potential longevity and impact within the broader academic community.

### **5.3.2 GCs Award Teams**

The GCs Award Teams represent a mosaic of interdisciplinary collaboration, each interweaving diverse academic disciplines with real-world societal issues. These teams, selected for their compelling projects, embody a shared goal: to address pressing societal questions through a scholarly and socially relevant lens.

The two Healthy Idaho awards were \$200,000 each, while the three RNS awards totaled \$400,000. The future of these Grand Challenge Teams extends far beyond the initial seed money they receive. This funding, while modest, serves as a catalyst, enabling teams to conduct pilot studies that lay the groundwork for more extensive future research. As LaRosa explains, the journey of these teams involves enhancing their understanding of the expertise required, expanding their partnerships, and eventually seeking larger funding opportunities from federal and state agencies and foundations (2023b, personal communication, September 25).

The Grand Challenge Award Teams are not just funding recipients but incuba-

tors of innovative ideas and collaborative partnerships. Central to the ethos of these teams is the requirement for transdisciplinary partnerships; each includes a strong community component. “Community is part of solving Grand Challenges that need social relevance,” she notes, highlighting the necessity of grounding academic research in real-world contexts (LaRosa, 2023b, personal communication, September 25). Including community partners in GCs’ research development aid in achieving goal 4, fostering a thriving community (Boise State University, 2024). It also aligns with the idea that academia must promote and support external community partnerships to tackle society’s wicked problems (Rittel & Webber, 1973) and achieve the United Nations’ SDGs. This transdisciplinary component is strategic, guiding the teams’ pilot research on trajectories with potential funding sources and societal impact areas.

### **Healthy Idaho Award Team: Wildfires and Urban Health**

Healthy Idaho Award 1 team, collaborating with St. Luke’s Health System in Idaho, is an excellent example of a commitment to advancing academic knowledge and addressing societal challenges in meaningful, impactful ways (Sadegh *et al.*, 2023). This team’s endeavor to explore the intersections of climate change and human health, particularly the impact of severe heat and wildfire smoke on vulnerable populations in Idaho, is a poignant illustration of research that resonates beyond academic circles (Sadegh *et al.*, 2023). This research’s focus on urban populations in Idaho contributes to global Sustainable Development Goals (SDGs) such as Good Health and Well-being by seeking to mitigate health risks associated with environmental factors (United Nations Department of Economic and Social Affairs, 2024). Additionally, it aligns with the Climate Action SDGs by addressing the broader implications of

climate change, including increased temperatures and wildfire incidences (United Nations Department of Economic and Social Affairs, 2024). The project's examination of the negative health effects of climate change offers insights valuable to Idahoans and other regions in the US experiencing similar environmental health challenges (Sadegh *et al.*, 2023). Such insights underscore the project's commitment to Partnerships for the Goals (United Nations Department of Economic and Social Affairs, 2024), demonstrating the potential for local research to inform wider-reaching solutions and foster regional collaboration (Sadegh *et al.*, 2023).

### **Healthy Idaho Award Team: Public Health Resiliency Building**

The Healthy Idaho Award Team 2, in partnership with the Wassmuth Center for Human Rights and the Idaho 97 Project, is pioneering an 18-month initiative aimed at countering violent extremism (VE) through innovative public health and social work practices across 12 communities in Idaho (Hutson *et al.*, 2023). This initiative, embodying the essence of a wicked problem, tackles the intertwined challenges of disinformation, social isolation, and potential violence, necessitating a multifaceted and nuanced approach that integrates education, legal, medical, and mental health sectors to forge community-driven prevention frameworks. The project's complexity is rooted in its causes' intricacy and solutions' lasting impacts, demanding bespoke strategies sensitive to local contexts and potential unintended consequences. Such a comprehensive strategy underscores the project's alignment with the SDGs, specifically targeting Good Health and Well-being by addressing health implications of VE, Peace, Justice, and Strong Institutions by fostering peaceful and inclusive communities and Partnerships for the Goals through its cross-sector collaboration (United Na-

tions Department of Economic and Social Affairs, 2024). This collaborative endeavor not only seeks to mitigate the immediate threats posed by VE but also contributes to the broader objectives of sustainable development by promoting well-being, justice, and strong institutional frameworks, reflecting a deep commitment to tackling one of society's most entrenched and complex challenges (Hutson *et al.*, 2023).

### **Resource Nexus Award Team: Idaho Regenerative Ranching and Carbon Projects**

The Idaho Regenerative Ranching and Carbon Projects, led by Jared Talley of the School of Public Service, address the wicked problem of aligning ranchers' economic interests with environmental stewardship through carbon sequestration and ecosystem restoration strategies (Research and Economic Development, 2024). This initiative targets SDGs such as Climate Action by enhancing soil carbon storage and Life on Land through ecosystem revitalization while also supporting Decent Work and Economic Growth by providing new economic avenues for ranchers (United Nations Department of Economic and Social Affairs, 2024). The complexity of this issue stems from the need to balance short-term economic benefits with long-term environmental sustainability, navigating the uncertain impacts of land management practices on carbon sequestration and ecosystem health, and embodying the interconnectedness of economic development, ecological balance, and community livelihoods (Research and Economic Development, 2024).

**Resource Nexus Award Team: Tribal Energy Solutions**

Stephanie Lenhart, an associate research professor in the School of Public Service, leads a project that exemplifies a collaborative model with community partners in research design and implementation aimed at enhancing energy and water resource sustainability in Idaho's remote and rural areas (Research and Economic Development, 2024). By building interdisciplinary capacity and a community network, this initiative directly supports SDGs such as Clean Water and Sanitation and Affordable and Clean Energy, particularly emphasizing the unique challenges and contributions of tribal communities (United Nations Department of Economic and Social Affairs, 2024). The project confronts the wicked problem of ensuring sustainable energy and water resources, which involves reconciling tribal knowledge and community needs with sustainable development practices. This effort highlights the critical role of inclusive, community-driven approaches in achieving long-term sustainability goals, reflecting the project's commitment to Partnerships for the Goals (United Nations Department of Economic and Social Affairs, 2024) by fostering partnerships that tailor solutions to the specific environmental and socioeconomic contexts of Idaho's tribal regions (Research and Economic Development, 2024).

**Resource Nexus Award Team: Refugee Farming Resilience**

The Refugee Farming Resilience initiative tackles the wicked problem of integrating refugee farmers into urban ecosystems, engaging with the complexities of agricultural adaptation, urban policy, and the integration of vulnerable populations. Led by Rebecca Som Castellano, the project directly contributes to the SDGs, such as Zero Hunger by promoting sustainable agriculture, Sustainable Cities and Communities

through the enhancement of urban ecological systems, and Reduced Inequalities by supporting the inclusion of refugee communities (United Nations Department of Economic and Social Affairs, 2024). The initiative's efforts to create actionable strategies for refugee farmers in collaboration with the city of Boise address the intertwined nature of social, economic, and environmental sustainability, reflecting the project's alignment with the broader aims of the SDGs to foster resilient communities and ensure inclusive participation in sustainable development practices (Research and Economic Development, 2024).

### **5.3.3 Interdisciplinary Research Advancement Teams**

At the heart of Boise State's ambition to elevate its research ecosystem, Interdisciplinary Research Advancement (IRA) teams engage in network interventions. These strategic efforts are crucial for cultivating a culture of interdisciplinary collaboration and driving the university's innovative research agenda forward. The Interdisciplinary Research Accelerator (IRA) training is a multifaceted program designed to augment the research capabilities of Interdisciplinary Research Advancement (IRA) teams. The IRA modules encompass three core engagement activities: Faculty Research Leadership, Strategic Visioning, and Team Science Training. Central to network interventions is developing strong research leadership, addressed through the Faculty Research Leadership module.

These network interventions began by selecting individuals in unique positions capable of catalyzing broader network structural changes. Glied *et al.* (2007) describe sustainable leadership characteristics of center directors as charismatic and capable of negotiating with administrators, department chairs, and center members. A transformational leader is dedicated to mentoring and sacrifices self-interests to align projects

and resources with the team's goals and priorities (Disis & Slattery, 2010). Bland *et al.* (2005) describe an ideal research leader as regarded highly as a scholar, sponsor, mentor, and peer model. When selecting interdisciplinary leaders, DRED nominated five well-positioned researchers, seasoned in their careers and capable of "floating all boats within a thematic area" (LaRosa, 2023b, personal communication, September 25).

These team leads then work with the CRCA to extend and build their team as part of the **Faculty Research Leadership** program. Conducted by the CRCA, this program focuses on enhancing research leadership skills and has two primary modules: Capacity Building and Strategy. The Capacity Building module exercises network and partnership development, encouraging faculty to forge interdisciplinary connections, spot research opportunities, and engage effectively in the grant proposal process (LaRosa, 2023a). Strategy sessions are consultative and aimed at refining the faculty's approach to research proposal development and strategic project planning (LaRosa, 2023a). This training sought to foster effective research collaboration and an inclusive culture of innovation and discovery.

The IRA network interventions encompass four primary network intervention categories: identification of pivotal individuals (nominate leads), segmentation into groups (build foundational team members), induction to foster interactions (develop relationships), and alterations to the network's structure (expand roster)(Vacca *et al.*, 2015; Valente, 2012). All three core IRA activities work to develop and protect the team's connections.

Team Leads work through the Faculty Research Leadership modules when attending "Office Hours," held by CRCA. Team Leads workshop teaming challenges

and receive planned leadership training (LaRosa, 2023b, personal communication, September 25). During the connective thinking process, team members may assume leadership roles as projects evolve (Disis & Slattery, 2010), aligning with DRED's approach that views all members as potential leaders and active participants in leadership development, contributing to the project's adaptability and success. LaRosa said in the interview, "It isn't necessarily the lead only who attends Office Hours. Whoever is on the team wants to do that kind of work is invited. We build a more distributed leadership structure this way" (2023b, personal communication, September 25). All members are potential leaders and active participants in leadership training, contributing to the project's adaptability and success. Such an approach may prevent issues when leaders must reduce their responsibilities or leave their positions, ensuring continuity and stability within the project (Glied *et al.*, 2007).

The second core IRA activity, **Strategic Visioning** (or Strategic Development and Road Mapping), is orchestrated by The Implementation Group (TIG) (LaRosa, 2023a). This initial phase of the IRA program aims to assist teams in articulating a coherent vision, mission, goals, and objectives (LaRosa, 2023a). It incorporated a consultative process beginning with surveys and interviews tailored to elucidate the individual and collective aspirations, challenges, and potential growth areas for team members (LaRosa, 2023a). The subsequent analysis of these interactions informed the strategic planning process, aligning the individual objectives of team members with their collective goals (LaRosa, 2023a).

The third core IRA activity, **Divergent Science**, is facilitated by external consultants Hannah Love and Ellen Fisher and offers six specialized activities tailored to the needs of the GCs teams or administrators (LaRosa, 2023a). This training covers

crucial aspects of team functionality, such as role clarity, project management, followership, communication, and decision-making, aiming to empower teams to tackle complex research problems effectively (LaRosa, 2023a). Each activity is designed not only to address the practicalities of team dynamics and administration but also to instill values of equity, diversity, and inclusion (LaRosa, 2023a).

Leaders are more successful with project management experience (Sonnenwald, 2007) and high levels of organization (Disis & Slattery, 2010). Project managers alleviate burdensome leadership responsibilities (Sonnenwald, 2007). The IRA teams are assigned a project manager who helps relieve minor administrative tasks (LaRosa, 2023b, personal communication, September 25).

In addition to this comprehensive access to the IRA professional development program, the IRA teams received a financial endowment (\$25,000). The strategic infusion of financial support and comprehensive, tailored training through the IRA program equips teams with resources and a transformative vision to expand their respective research networks across the institution. These network treatments should result in a robust foundation for grant application(s) to fund the infrastructure of an emerging research center, facilitating its trajectory toward becoming an innovative research hub within Boise State.

### **IRA Food and Fiber Systems**

The IRA team, led by Som Castellano *et al.*, zeroes in on the complex sustainability issues within Idaho's food and fiber systems, facing ecological, social, and economic challenges. Concentrating on the agrifood system's entirety—from production and processing to marketing, consumption, and waste—the team aims to uncover and

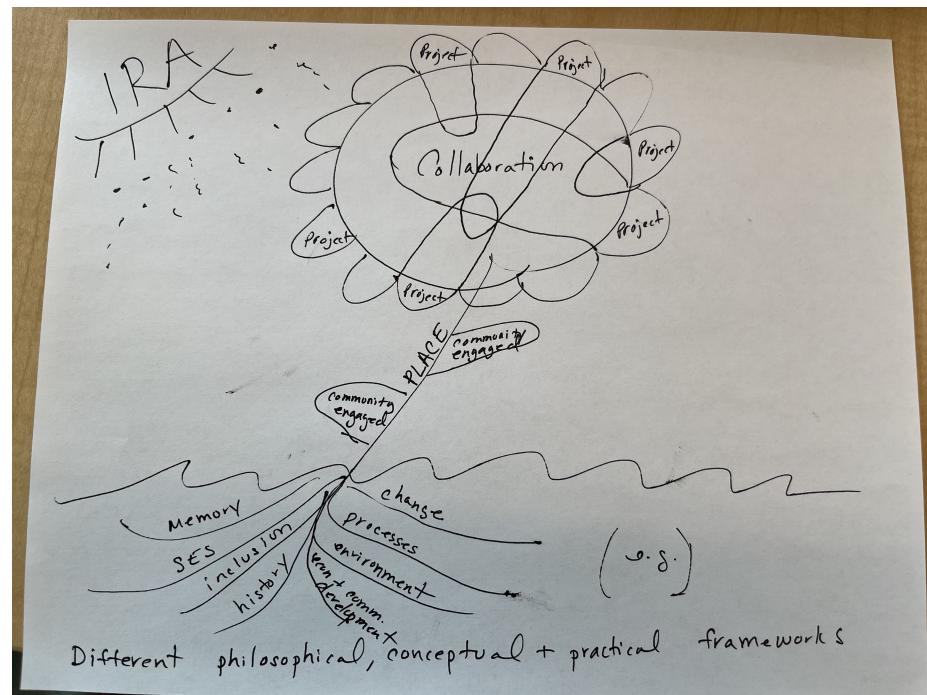
address sustainability obstacles such as significant contributions to climate change, soil erosion, and exploitation of resources and labor (Som Castellano *et al.*, 2022). These intricate challenges they tackle are emblematic of wicked problems due to their ecological, social, and economic interconnectedness and the complex repercussions each solution might generate (Rittel & Webber, 1973). This multifaceted problem defies straightforward solutions, as addressing one aspect can inadvertently affect another, necessitating a nuanced approach that considers stakeholders' diverse and often conflicting interests, including marginalized voices like small-scale producers and laborers. The team's work navigates the ecological changes and their intersections with political, economic, social, and cultural dimensions to emphasize the empowerment of these marginalized voices (Som Castellano *et al.*, 2022). This approach fosters a comprehensive understanding of these systems' sustainability challenges and opportunities, guiding them toward meaningful policy changes and innovations for sustainability (Som Castellano *et al.*, 2022).

### **IRA Materials Resources Sustainability Nexus (MARESUNEX)**

The IRA MARESUNEX team at Boise State is committed to fostering a sustainable and equitable materials economy through innovative solutions in Idaho (Crowley *et al.*, 2022). Their work aims to balance ecological sustainability, social justice, and economic viability, focusing on the lifecycle of materials from sourcing to disposal, informed by STEM disciplines (Crowley *et al.*, 2022). Central to their mission is developing partnerships that bridge rural communities' values and traditions with scientific and technological advancements (Crowley *et al.*, 2022). These collaborations focus on mining communities that are pivotal in extracting critical battery elements,

aiming to integrate public inputs for better regional outcomes (Crowley *et al.*, 2022). MARESUNEX initiatives include creating educational and career pathways in STEM for rural students, working with industry to support the green energy economy, and engaging in policy discussions to ensure that development considers the needs and impacts of local and regional communities (Crowley *et al.*, 2022). By emphasizing inclusivity and respect for diverse populations, the team dismantles barriers. It fosters mutual engagement between rural and urban communities, thus contributing to the global pursuit of environmental sustainability and justice for all involved parties (Crowley *et al.*, 2022).

### IRA Placemaking



**Figure 5.1:** The white paper by the IRA Placemaking team presents an illustrative conceptual diagram that metaphorically represents the structure and function of their interdisciplinary thematic space.

The Placemaking team created a different kind of white paper, which was interpreted in this analysis. At the roots, they have foundational elements such as memory, socioeconomic status (SES), inclusion, history, economy, community development, environment, process, and change. These roots may signify the deep-seated factors that nourish and sustain the “place” that forms the stem, indicating the central focus of their efforts on the physical and social aspects of community spaces. The leaves, denoting community engagement, suggest the organic growth and outreach necessary for the projects to thrive. The petals represent disciplines, and the core of the flower, where these disciplines converge, symbolizes the notion that collaborative efforts are central to the team’s initiatives, with diverse projects branching out from this collaborative hub. The sun, labeled as the IRA training modules, shines over the entire structure, suggesting that the IRA’s guidance and resources are the light that energizes and supports the team’s growth and flourishing. The title “Different philosophical, conceptual + practical frameworks” implies that various theoretical and methodological approaches underpin the projects, each tailored to address the unique aspects of placemaking within their contexts.

This artistic representation encapsulates the complexity of Placemaking, highlighting that it is not only multidimensional, encompassing various social and environmental factors, but also dynamic, requiring ongoing engagement and adaptation. The image communicates that the IRA Placemaking team’s work is deeply rooted in community and environment, seeking to create sustainable and inclusive places through a collaborative, well-supported research and action process.

### **IRA Use-Inspired Science to Inform Practices (USIP)**

The USIP team promotes sustainable land management and fosters community well-being through science-driven practices. Central to their approach is the integration of local knowledge with the capabilities of private and government sectors to innovate natural resource and human capital management (Forbey *et al.*, 2022). By engaging academia, government, and industry, the team aims to generate science-informed solutions, develop a skilled workforce, and transform systems into inclusive, sustainable practices (Forbey *et al.*, 2022). This collaborative effort aligns with the NSF's goal of advancing global STEM innovation. It is geared towards catalyzing structural changes within partner organizations, overcoming implementation barriers, and defining future workforce competencies (Forbey *et al.*, 2022). During the 2023 spring semester, they were focused on forging ties with NGOs and private entities, leveraging use-inspired research to prepare a career-ready STEM workforce and create innovation-conducive environments, particularly in the natural resources sector (Forbey *et al.*, 2022).

### **IRA Water Energy Human Systems**

The IRA Water Energy Human Systems team is shaping a sustainable future for the American West's water-energy-human nexus, emphasizing harmony in a region undergoing climatic and social shifts (Flores *et al.*, 2022). Their work involves partnering with communities affected by the legacies of settler colonialism to co-develop solutions for water quantity and quality challenges exacerbated by climate change (Flores *et al.*, 2022). The team seeks to reconcile the region's environmental signals, like diminishing snowpacks and erratic precipitation, with the need for equitable resource

management (Flores *et al.*, 2022). By advancing predictive capabilities for water systems and integrating diverse data into community-specific knowledge systems, they aim to facilitate informed decision-making and equitable, just resource distribution in the Intermountain West's varied economic and social landscape (Flores *et al.*, 2022).

## 5.4 Methods: Outcome Measures

Leite & Pinho (2017) outline typical research process inputs and outputs. Inputs, including human and financial resources, infrastructures, and the body of existing knowledge, lead to outputs ranging from generating new knowledge to tangible products like articles, book publications, patents, and researcher professional development programs (Leite & Pinho, 2017, p. 94). The GCs' investments hope to result in an increased output of interdisciplinary scholarly work.

Leite & Pinho (2017, p. 94) emphasize that different teams aim to produce different outputs, making measuring productivity challenging. The LOVE teams differ in network treatments and outcome goals.

### 5.4.1 Team Treatment and Outcome Differences

Distinct differences in network treatments and outcome goals delineate the approaches tailored to Leadership, Award, and IRA teams. Each category is uniquely supported, reflecting varied paths to fostering innovation and interdisciplinary collaboration across campus.

As described by LaRosa (2023a), IRA teams receive specialized training and nominal funding, focusing not on immediate project development but on cultivating a thematic network poised for significant future proposals. The objective for these teams is ambitious—securing substantial center funding, such as NSF Science and Technol-

ogy Center awards, necessitating a demonstration of a comprehensive network and research capability (LaRosa, 2023b, personal communication, September 25).

In contrast, award teams receive substantial funding for specific pilot projects without the targeted training IRA teams receive. Award teams aim to leverage these pilot studies towards securing larger, external grant funding, a direct pathway to expanding their research endeavors beyond initial university support (LaRosa, 2023b, personal communication, September 25).

While central to guiding the GCs initiative, the leadership teams do not receive focused training or financial backing as IRA or Award teams. Instead, their influence is more strategic, shaping the initiative's goals. The CRCA offers team science training to all faculty, enhancing collaborative skills throughout the university. However, participation in the specialized IRA program is reserved for IRA teams (LaRosa, 2023b, personal communication, September 25).

Because each team has its own outcome goals, each is treated as a case study, advocating for personalized measures of success. Competition between teams might inadvertently promote differentiation and specialization instead of cross-team collaborations (Duysburgh *et al.*, 2012, p. 276). Leite & Pinho (2017, p. 90) recommend a participatory productivity evaluation process tailored by each team and their stakeholders. They emphasize the importance of re-evaluating as the team evolves and fostering a universal culture of collaboration through ongoing dialogue and assessment (Leite & Pinho, 2017, p. 90). The SNA metrics outlined in the subsequent sections offer methodologies for evaluating research network productivity.

### 5.4.2 Scientific Productivity

An increase in collaborative grant proposals, awards, joint publications, committee involvement, conference participation, and university business measures scientific productivity. The LOVE survey asked participants about their previous professional interactions with teammates, forming networks: Joint Publications, Conferences, Grant Proposals, University Business, and Committees. These networks illustrate the team's prior creative work activities with each other before the team formed. Following the survey's repetition, SNAP can compare changes in density and average degree over time, measuring the change in the volume of the teams' productivity. The subsequent analysis will detail and compare these networks.

As discussed in the literature review, understanding how team members will contribute poses a significant challenge to interdisciplinary research (Dalton *et al.*, 2022; Piqueiras *et al.*, 2023; Duysburgh *et al.*, 2012). This challenge is echoed by Boise State faculty in qualitative research, where a faculty member expressed difficulty in identifying areas of overlap among disciplines. The LOVE survey participants were asked to rate their understanding of how each team member will contribute to the research team. From this, an Understanding How network is created and analyzed. This network tells of the team's ability to co-create and is a valuable predictor of the team's future productivity.

The Professional networks (Joint Publications, Conferences, Grant Proposals, University Business, and Committees) will measure each team's Scientific Productivity between each other, which is tracked over time. A higher density in these networks implies a more robust pattern of collaboration, suggesting an environment conducive to scientific productivity. Therefore, by tracking density over time, SNAP

can discern trends in collaborative behavior, using it as a benchmark to compare the evolving nature of professional interactions within the network. A higher average degree in these networks indicates more extensive collaboration and interaction among team members. Monitoring changes in average degree over time can provide us with a clear understanding of evolving collaboration patterns, with an expected increase aligning with GCs research teams' growing interconnectedness and collaborative efforts.

The historical grant proposal data shows another measure of the team's scientific productivity before joining the team. The 5-year network degree centrality illuminates previous collaborative proposals for each team member. This historical grant proposal network (CUPID) differs from the Grant Proposals network created by the survey as the historical data tells of the individuals' collaborations with any faculty at Boise State, not simply collaborations between team members.

Aside from these conventional SNA metrics, exploring innovative methods for a deeper understanding of scientific productivity within the LOVE teams could be valuable. One such method, Power Graphs, as introduced by Panagopoulos *et al.* (2017), presents an advanced approach to quantifying the creative output of faculty members or research groups. Panagopoulos *et al.* demonstrates this method using ego networks of publication and grant proposal to detect "rising star" individuals and teams. Utilizing both CUPID and CATNIP networks, Power Graphs could highlight the collaborative endeavors of teams. While this thesis employs a different methodology, the potential application of Power Graphs in future research phases promises to enrich the understanding of how collaborative efforts evolve, especially in capturing long-term outcomes.

Exploring scientific productivity through collaborative networks sets the stage for examining the broader impacts of the GCs' investments, particularly their role in nurturing resilient research teams capable of enduring challenges and adapting over time. This focus on resilience, essential for long-term success and adaptability, bridges the discussion from measuring productivity to assessing teams' sustainability and growth potential under the GCs initiative.

### 5.4.3 Team Resilience

Beyond immediate creative outputs, the GCs' investments aim to foster research teams characterized by enduring resilience and adaptability. The durability of the case study team analyzed by Love *et al.* (2021) over 15 years, marked by team membership expansion, mentorship, and positive interpersonal relationships, exemplifies the resilience sought. These attributes are central to the resilience strategies addressed by the IRA network interventions.

Exploring the strategic recruitment and selection for GCs research teams reveals the complexity of fostering interdisciplinary research (e.g., Bednarek *et al.*, 2023; Duysburgh *et al.*, 2012; Sonnenwald, 2007). The challenge of learning across disciplines in a constrained timeframe may deter prospective members (Piqueiras *et al.*, 2023). The IRA network interventions address these variables for the IRA teams but not the leadership or award teams. SNAP's subsequent study phases can compare teams who received and did not receive the IRA intervention. The study lays the foundation to measure team composition characteristics and interpersonal relationship changes.

Strategic recruitment contributes to team resilience by bringing diverse perspectives and skills necessary for long-term success. However, team member recruitment

should be broader than prospective researchers with interests that directly align with the team's long-term goals. As Bednarek *et al.* (2023, p. 9, 11) suggest that the allure for potential team members often stems from broad research interest, which evolves into a passion for the team's mission.

Building on qualitative findings that mutual interests are crucial for initiating collaborations, these interests often translate into reciprocation that might not always be visible through shared publications but can manifest in exchanging ideas, division of labor, or advisory roles (White, 2011). Within this context, mentorship plays a pivotal role, bridging the interdisciplinary complexities that research teams frequently encounter, facilitating a more seamless integration of diverse disciplinary perspectives, and enhancing the overall collaborative process.

### New and Expanded Opportunities Across Campus

The pivotal role of mentorship within the GCs initiative is crucial in enhancing educational access and fostering a collaborative research culture, aiming to create a fair, equitable, and accessible environment for all campus community members. The significance of mentorship in fostering collaborative research is highlighted by Norton *et al.* (2017, p. 9, 12), uncovering that the chance for mentorship by well-connected team members significantly motivates collaboration. Even though 30% of their survey respondents recognized mentorship as a key factor for collaboration, only 4% viewed mentoring others as a motivation for collaboration (Norton *et al.*, 2017, p. 12). This disparity underscores the need for teams to excel in providing mentorship, enhancing the appeal of joining a research team, and fostering a learning and mutual growth culture.

Aligned with Boise State's strategic goals, particularly in enhancing educational access (Boise State University, 2024), the GCs initiative's mentorship model plays a pivotal role in student education. A mentorship model explored by Love *et al.* (2021) underscores the substantial benefits for team members from various educational stages, from undergraduates to postdocs. This model facilitates personal and professional growth among team members. Notably, this approach has been shown to encourage student researchers to become core contributors to scientific productivity, illustrating the transformative impact of mentorship on team dynamics and individual careers (Love *et al.*, 2021).

The qualitative analysis in Chapter 3 identified student researchers as important but challenging collaborators as they require significant investments compared to the return and period of the relationship. Including junior faculty researchers will also benefit the GCs teams because they are better equipped to extend the senior researchers' lines of thought White (2011, p. 274) and bring fresh perspectives and innovative ideas Valente (2012). Strategic goal 4 aims to enhance employee well-being and career growth by advancing the learning and working environment and responsibly using university resources to support collaboration across campus (Boise State University, 2024).

By implementing a strategic approach to team composition and mentorship, the GCs initiative not only seeks to enhance interdisciplinary collaboration but also sets the stage for exploring how these efforts contribute to broadening opportunities for engagement and growth across the university. The following discussion will further examine the initiative's impact on fostering an equitable and inclusive research community.

With the selection of seasoned faculty as leaders, there is a concern that the GCs' investments may not benefit campus researchers. LaRosa articulated this by saying, "Any time an initiative holds resources for a specific venture, faculty may think that it is intended to empower the powerful and not extend to faculty as a whole" (2023b, personal communication, September 25). Additionally, the blueprint for Boise State's success calls for the promotion of a fair, equitable, and accessible environment for all members of campus to make a difference (Research and Economic Development, 2024). Therefore, the SNAP project aims to assess if the GCs initiative effectively broadens engagement opportunities across campus, ensuring that all interested faculty members can participate and contribute.

Sonnenwald (2007, p. 8) highlights how collaborations among well-established researchers may form powerful lobbying groups that influence research policy and funding decisions, often to their advantage. This phenomenon is echoed by Disis & Slattery (2010), who note that the most vocal and established researchers frequently and disproportionately secure more resources. Such practices challenge the objectives of the GCs initiative by potentially concentrating intramural funds among those already skilled in acquiring extramural funding rather than expanding the university's overall capacity for securing significant external grants. A strategic allocation of resources is essential to counteract this tendency and the risk of perpetuating systemic biases. The strategy empowers a broader range of researchers to develop grant acquisition skills, enhancing the university's research capacity and fostering a mentorship culture. The mentor-mentee analysis determines whether the GCs initiative's selection process equitably positions individuals to drive new and expanded collaborative opportunities across campus, thereby aligning with Boise State University's broader

goals of promoting inclusive growth and collaboration.

This section outlines an approach for analyzing team membership characteristics, with a focus on emphasizing mentorship and experiential diversity within research teams. The analysis applies SNA methodologies to establish a baseline of the current state of research team dynamics. Detailing this methodological preparation ensures a robust foundation for subsequent evaluative analysis, aiming to assess the initiative's effectiveness in promoting mentorship within the academic community.

This thesis assesses team members' capacity for facilitating mentor-mentee relationships and expanding opportunities across campus by considering their experiential diversity. This process involves several methods, including examining the diversity of team members' positions at Boise State. Bland *et al.* (2005) point out that faculty of higher rank are more likely to have a history of high research productivity because it is a significant criterion for promotion. Survey participants were asked to select their connection to Boise State and allowed to select from the following 15 options: Assistant Professor, Associate Professor, Professor, Lecturer, Assistant Clinical Professor, Associate Clinical, Clinical Professor, Assistant Research Professor, Associate Research Professor, Research Professor, Emeritus Professor, Professor, Professional Staff, Classified Staff, Post-Doctoral Staff, Community Member, Other. If "Other" was selected, the participant could type their connection to the university in a text box. Teams should contain members from a range of positions, from students to full professors, to ensure there is various research productivity experience.

Furthermore, the analysis delves into team members' grant proposal writing experience, utilizing centrality measures in the university-wide grant proposal network (CUPID) to discern prestige and power within the research community. Such mea-

sures reveal team members' range of influence and potential mentorship capacity (White, 2011, p. 274). Teams exhibiting a broad range of centrality measures likely embody a blend of well-established researchers and emerging scholars, fostering an environment ripe for mentorship and collaboration. However, if most team members have high centrality measures in the historical grant proposal network, the GCs' investments will likely empower the powerful. In this situation, teams should add more mentee members to obtain experiential diversity.

In assessing the role of mentorship within research teams, the study leverages the concept of indegree and outdegree centrality in social network analysis to quantify mentor-mentee dynamics. According to Norton *et al.* (2017, p. 10-11), high-status researchers are frequently sought for advice by others, who, in turn, are also sought after for advice, establishing a hierarchical structure of expertise and influence. This definition underpins the rationale for using indegree as a measure of mentorship within the "My Mentor" and "Advice" networks. In these contexts, **indegree** represents the number of times an individual is nominated as a mentor or source of advice, indicating their status as a valued mentor within the network. High indegree values signify that a researcher is a pivotal source of guidance and knowledge, embodying the qualities of an experienced and influential mentor.

Conversely, **outdegree** in the "Their Mentor" network reflects the extent to which an individual nominates others as mentees, providing insight into the distribution of mentee-seeking behavior within the team. A higher outdegree indicates active seeking of mentees, highlighting the relational dynamics from the perspective of mentors. Similarly, indegree measures team members' status as a valued mentee.

Team characteristics should be not only experience-level diverse but also inter-

disciplinary. The following section details the planned method for evaluating team characteristics to understand the current discipline diversity of the teams, emphasizing the need for both experience-level diversity and interdisciplinarity.

### **Interdisciplinary Collaboration**

Interdisciplinarity is a core requirement for the GCs teams (LaRosa, 2023b, personal communication, September 25), necessitating a comprehensive methodological framework to assess the extent of interdisciplinary composition and integration within these teams. Evaluating the teams for interdisciplinary distance involves categorizing team membership across a spectrum of within-discipline, short-distance, and long-distance interactions (Bolger, 2021), aiming for a balance that fosters diverse and innovative collaborations.

The survey's name-generator question emerges as a tool for addressing the challenge of conceptualizing research within an expansive interdisciplinary framework. This approach encourages participants to nominate significant contributors beyond the provided roster, thereby gauging the team's orientation towards either a disciplinary or a transdisciplinary collaboration model. Including external nominees offers valuable insights into the teams' ability to transcend disciplinary boundaries.

The survey name-generator results may indicate a necessity for strategic network interventions to overcome conceptual barriers in recognizing potential interdisciplinary collaborators. Strategic network interventions, as outlined by Valente (2012) and Vacca *et al.* (2015), can also aid in fostering a thriving community at Boise State University (2024). Valente outlines tactics such as adding or deleting nodes and links or rewiring existing connections to optimize network structure. Vacca *et al.* (2015)

apply these tactics to a university's scientific collaboration networks to facilitate network interventions. Vacca *et al.* use co-authorship and grant proposal networks to identify unconnected researcher groups, shown as modular structures within network visualizations. They demonstrate the use of the four primary network interventions to enhance the university's network's overall structure while also assembling cross-disciplinary teams (Vacca *et al.*, 2015).

While identifying and connecting researchers from various disciplines is crucial, achieving true interdisciplinary collaboration requires a deeper level of integration, termed **convergence**. In the context of interdisciplinary collaboration, convergence refers to the process by which team members from diverse disciplinary backgrounds overcome different discipline incompatibilities through a shared understanding and mutual adaptation (Dalton *et al.*, 2022, p. 8).

In Bolger's (2021) study of interdisciplinary research centers, he focuses on the convergence of researchers of multiple disciplines. Bolger (2021) does this by surveying the faculty of three well-established research centers, each at a different institution. He found that researchers from the humanities and social sciences were "add-ons" and not fully part of defining questions or generating sustainability research (Bolger, 2021, p. 14). While developing integrated, interdisciplinary knowledge is notably tricky for long-distance collaborations, obtaining grant funding makes it necessary to overcome these hurdles. LaRosa underscores the critical need for authentic interdisciplinary collaboration to meet federal funding requirements, highlighting the challenge of integrating STEM and social sciences to foster genuine co-creation of research questions (2023b, personal communication, September 25).

Teams need convergence not only to acquire funding but also to have team re-

silence. Bednarek *et al.* (2023, p. 10) identified that research membership “stickability” begins with embedding team members into the respective research projects. From the literature review, it is safe to say that convergence is challenging for interdisciplinary teams.

To effectively measure the success of convergence efforts, several network metrics—Out Degree and Betweenness—are utilized within the Knowledge Of network to quantitatively assess the level of disciplinary integration and mutual comprehension among team members. These metrics offer insights into the extent to which team members understand each other’s fields. The teams’ degree of interdisciplinarity is essential when interpreting these metrics. Teams with a higher proportion of within-discipline relationships will, by default, have knowledge of their team members’ disciplines, which does not contribute to the convergence of disciplines.

In the Knowledge Of network, Out Degree centrality accurately reflects individuals’ comprehension of their colleagues’ areas of expertise, underscoring the depth of their awareness and grasp of the team’s collective capabilities. High Out Degree centrality indicates a thorough understanding of multiple team members’ specific disciplines, crucial for fostering interdisciplinary collaboration within teams characterized by diverse academic backgrounds. Betweenness centrality gauges a member’s role in bridging diverse knowledge areas, with high scores indicating key individuals who facilitate integration across disciplinary gaps. Low betweenness might imply direct knowledge exchange among members, indicative of a cohesive team understanding.

These metrics collectively assess the depth of interdisciplinary integration, the effectiveness of knowledge sharing, and the quality of mutual understanding within teams, underscoring the importance of discipline diversity for genuine interdisciplinary

collaboration. For the pre-treatment Knowledge Of network, it is predicted that individuals with high Out Degree centrality are likely in the Professor position or are part of teams with a predominance of within-discipline relations.

### **Interpersonal Relationships**

The path to effective collaboration often lies in the informal, interpersonal connections that develop over shared experiences, such as lunchtime conversations (Disis & Slattery, 2010). The Personal network aggregates Personal Advice, Hang Out, and Personal Friend networks. Strong ties are often associated with more substantial social support and influence (Borgatti *et al.*, 2022, p. 5). The weight is interpreted as the strength of the relationship. In the context of the GCs initiative, the strength of a faculty member's ties could be predictive of their ability to garner resources and support.

Within the Personal network, degree centrality quantifies the extent of personal interactions among team members. A uniform degree distribution indicates a balanced engagement level among the team, with no person being significantly more central or isolated than others regarding personal interactions. Consequently, a researcher with a higher degree relative to others signifies a greater involvement in more personal interactions, highlighting their pivotal role in fostering social connections within the team.

Betweenness centrality identifies individuals who act as bridges within the social structure of the team, facilitating interactions between team members who may not directly connect. High betweenness would indicate a key role in social cohesion and the diffusion of social capital. The individual may have unique roles within the team's

personal interaction network. When most individuals in a network have a betweenness centrality of zero, it suggests that the network does not have points through which personal interactions must pass.

The Outcome Measures section meticulously articulated a methodological framework for assessing the GCs initiative's impact at Boise State. The initiative aims to enhance scientific productivity, mentoring, transdisciplinarity, convergence, and interpersonal relationships within each research team. By delineating the specific network treatments and goals for Leadership, Award, and IRA teams, this framework underscores the complexity of evaluating productivity against diverse team objectives. The strategic focus on fostering an environment conducive to interdisciplinary collaboration, mentorship, and developing resilient research communities forms the crux of the anticipated outcomes.

In the analysis section, the emphasis will be on applying SNA to scrutinize these identified variables in depth. This approach will enable a granular examination of how GCs' investments influence research collaboration at the university. The forthcoming analysis is poised to unravel the initiative's efficacy in promoting an equitable, inclusive, and innovative research landscape by measuring the initial state of the outlined variables. By exploring the dynamics of scientific productivity, assessing the richness of experiential diversity, understanding the depth of mentoring interactions, gauging the breadth of interdisciplinary collaboration, and analyzing the strength and quality of interpersonal relationships, this section aims to provide actionable insights into the transformative potential of the GCs initiative at Boise State.

## 5.5 Analysis

The comprehensive exploration of the previous interactions within Team J at Boise State focuses on the nuances of network interactions, the dimensions of scientific productivity, and the attributes of team resilience. This section serves as the map of the measuring methods for team success.

The first domain, Network Interactions, provides a nuanced understanding of both “Professional” and “Personal” multilayer networks through the lens of Von Neumann entropy. This section dissects the complex interplay of social and professional connections and how these layers contribute to the team’s scholarly pursuits.

Moving to the second domain, the analysis then shifts focus to Scientific Productivity, exploring the intricate relationships that potentially drive scholarly output and innovative research within the teams. This section aims at online techniques that investigate academic engagement that aids in future productivity and intellectual vigor.

The third domain, Team Resilience, contemplates the robustness and adaptability of the teams. It encompasses analysis of faculty positions, department affiliations, the intricacies of mentoring and advice networks, the knowledge of peer investigators, and the personal connections that bind the team. This domain also considers the implications of roster expansions on the team’s cohesive strength and the ability to persist and grow.

To prevent the cultivation of a competitive environment and to honor the unique objectives of each group, the thesis treats each team as a case study, advocating for bespoke measures of success. Team J serves as the focal point of this analysis, with anonymity preserved through randomized labeling to protect member identities. Detailed visualizations and statistical tables for all teams are accessible via links to

supplementary HTML documents in Appendix ?, providing a comprehensive repository of data without compromising confidentiality. This pre-treatment analysis stands independent of future treatment comparisons, laying the groundwork for subsequent phases of the SNAP study to benchmark the effects of various interventions on team dynamics and performance.

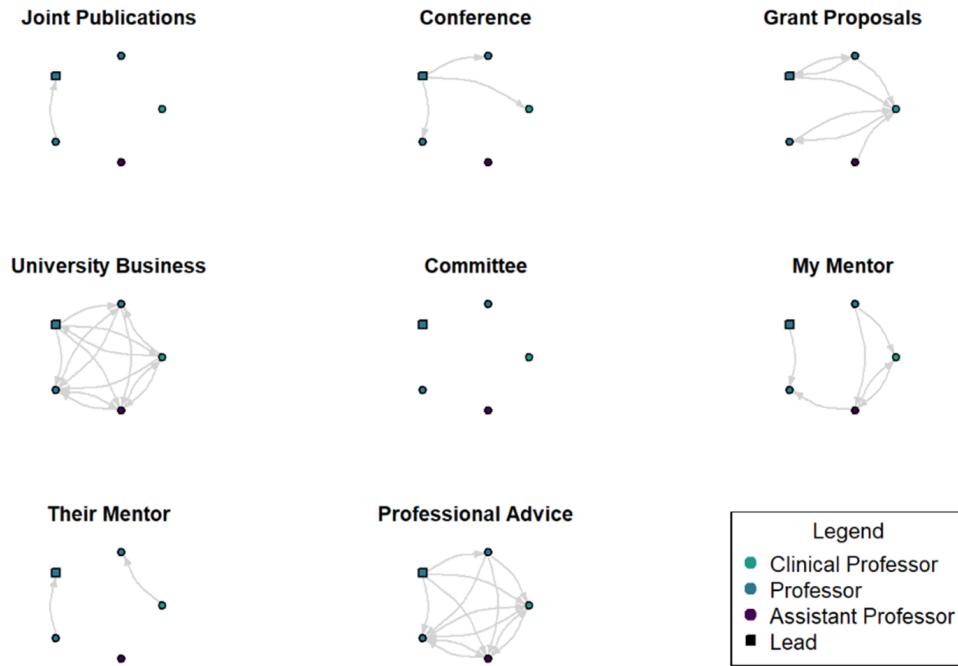
### 5.5.1 Network Interactions

The multilayered networks under examination, Professional and Personal, encompass a composite of single-valued ties, each encapsulating a distinct form of professional or personal interaction within the team. The analysis herein adheres to the procedures laid out by Domenico *et al.* (2015) to maintain maximal informational content while contemplating layer reduction. The behavior of these networks is nuanced; strongly coupled layers bear unique characteristics when contrasted with aggregated or singular networks, impacting their significance within the larger social structure. This section scrutinizes each layer's individual contributions and their collective influence on the professional and personal network's framework, employing aggregation where appropriate to streamline the analysis. By examining the entropic measures of these networks, insights into the structural dynamics and the evolution of professional and personal interactions are gleaned, enhancing the understanding of collaborative climates within multilayered social systems.

#### Professional Network

The “Professional” multilayered network is comprised of aggregated single-valued ties and embodies a range of activities encapsulated in sub-layers such as joint publications, conference attendances, grant proposal collaborations, involvement in univer-

sity business, committee participation, mentorship roles, and professional advice.



**Figure 5.2: Professional Sub-Layer Networks of Team J:** This figure delineates the various academic and professional interactions within Team J, categorized into sub-layers corresponding to distinct collaborative activities such as publications and administrative tasks. Consistency in participant positioning across sub-layers facilitates comparative visual analysis. The square node denotes the team lead, while the color-coding of nodes corresponds to the academic rank of the faculty members, as detailed in the legend. Edges are curved to indicate the direction of the interactions.

The networks depicted in Figure 5.2 showcase various forms of academic and professional engagements between Team J members. Each node and link in the network corresponds to a member and their interactions across several domains: joint publications, conference engagements, grant proposal collaborations, university business, committee involvement, mentorship dynamics, and exchanges of professional advice. The ‘University Business’ and ‘Professional Advice’ networks manifest as the most

densely connected sub-layers, indicative of a vigorous exchange of knowledge and administrative collaboration among team members. In contrast, the 'Committee' sub-layer is characterized by its absence of connections, which may suggest a more individualistic or siloed approach within this context. The 'Grant Proposals' sub-layer indicates a substantial level of collaborative effort in seeking funding, which is pivotal for sustaining research activities. It is also essential to note that the networks are directed, with the directionality of relationships illustrated by curved edges. These curves facilitate the distinction between unidirectional and reciprocal interactions, thus providing deeper insights into the nature of professional exchanges among the members.

**Layer Aggregation Analysis** Similar networks are commonly aggregated to reduce the number of networks managed (e.g., Baggio *et al.*, 2016) However, networks that are dissimilar-edged should not be aggregated. Identifying the optimal configuration that amplifies  $q(\lambda)$  poses a computationally challenging problem, necessitating the evaluation of all potential layer partitions, a task intractable for networks with a considerable number  $M$  of layers (Lee *et al.*, 2012). In response to this computational complexity, (Domenico *et al.*, 2015) employs a hierarchical clustering approach.

To streamline a multilayer network into a more manageable form, (Domenico *et al.*, 2015) propose a method utilizing the quantum Jensen-Shannon divergence (JSD)—a concept borrowed from quantum information theory to gauge the (dis)similarity across network layers. The objective of the aggregation procedure is to optimize the relative entropy  $q(\lambda)$ , epitomizing the layers' distinctiveness relative to an aggregate network. This technique iteratively merges layer pairs with the minimal quantum JSD, successively condensing the network. It prioritizes amalgamating analogous lay-

ers to preclude the insertion of spurious structural features. The end result is a dendrogram—a tree-like diagram—that elucidates the layer aggregation sequence. Each dendrogram leaf symbolizes an original layer, while internal nodes denote merged layers, culminating in the root that represents the fully integrated network.

In concordance with (Domenico *et al.*, 2015), layers are then amalgamated incrementally, according to the formula:

$$JSD(P \parallel Q) = 0.5 \times (KL(P \parallel R) + KL(Q \parallel R)) \quad (5.1)$$

The JSD is quantified using the ‘philentropy’ package (Drost & Nowosad, 2023) in RStudio (RStudio Team, 2020). The examination of the JSD matrix provides valuable insights into the similarity between pairs of network layers within the Professional sub-layer networks. The diagonal of the matrix is populated with zeros, signifying the divergence of each layer with itself is naturally non-existent. The focus thus shifts to the smallest non-zero value within this matrix to identify the pair of layers with the greatest similarity. Network layers devoid of edges are exempt from this assessment. For instance, the “Committee” sub-layer, which lacks connections in the team under study, is consequently omitted.

Upon analysis of Table 5.1, the JSD of 0.1849 emerges as the smallest non-zero value, occurring between the “University Business” and “Professional Advice” network layers. This indicates that among all the layer pairs, ‘University Business’ and ‘Professional Advice’ exhibit the highest degree of similarity according to the Jensen-Shannon metric.

The heatmap complemented by a dendrogram (Figure 5.3) offers an insightful visualization of the JSD among the layers within Team J’s Professional network.

|                     | <b>Joint<br/>Pub</b> | <b>Conference</b> | <b>Grant<br/>Prop</b> | <b>BSU<br/>Business</b> | <b>My<br/>Mentor</b> | <b>Their<br/>Mentor</b> | <b>Professional<br/>Advice</b> |
|---------------------|----------------------|-------------------|-----------------------|-------------------------|----------------------|-------------------------|--------------------------------|
| Joint Pub           | 0.0000               | 1.0000            | 1.0000                | 1.0000                  | 1.0000               | 0.3113                  | 1.0000                         |
| Conference          | 1.0000               | 0.0000            | 0.5803                | 0.5918                  | 0.7704               | 1.0000                  | 0.5716                         |
| Grant Prop          | 1.0000               | 0.5803            | 0.0000                | 0.6064                  | 0.6918               | 1.0000                  | 0.3841                         |
| BSU Business        | 1.0000               | 0.5918            | 0.6064                | 0.0000                  | 0.4754               | 0.8447                  | 0.1849                         |
| My Mentor           | 1.0000               | 0.7704            | 0.6918                | 0.4754                  | 0.0000               | 1.0000                  | 0.3425                         |
| Their Mentor        | 0.3113               | 1.0000            | 1.0000                | 0.8447                  | 1.0000               | 0.0000                  | 1.0000                         |
| Professional Advice | 1.0000               | 0.5716            | 0.3841                | 0.1849                  | 0.3425               | 1.0000                  | 0.0000                         |

**Table 5.1: Jensen-Shannon Distance Matrix for Professional Sub-layer Networks.** The matrix quantifies the divergence between pairs of network layers, with the smallest non-zero divergence value highlighting the most analogous pair. Here, the ‘University Business’ and ‘Professional Advice’ networks demonstrate the closest similarity, as reflected by the minimal divergence score.

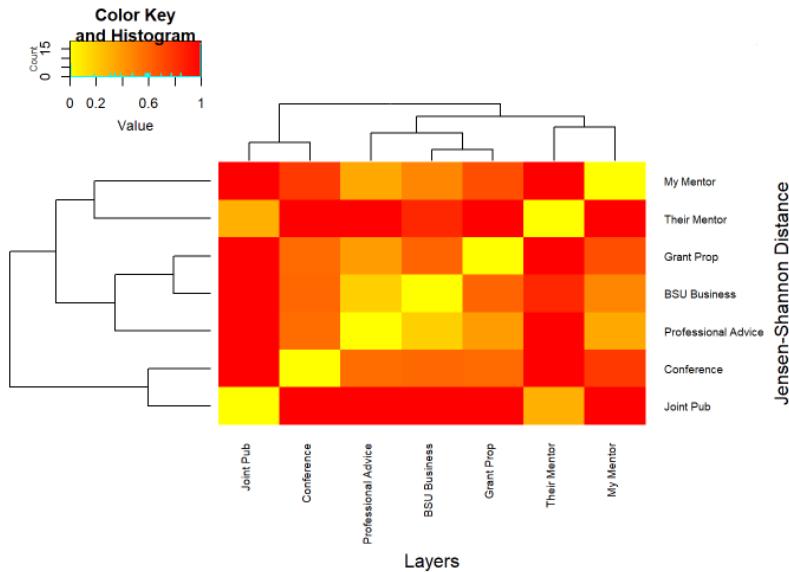
Each matrix element represents the divergence between a pair of layers, with the color intensity denoting the degree of dissimilarity in professional interactions.<sup>1</sup>

The central cells along the diagonal exhibit the lightest hue, indicating zero divergence, as expected when layers are compared with themselves. Progressing outward from the diagonal, the color gradient transitions to deeper shades, with the most intense red signaling the greatest divergence. The juxtaposition of “My Mentor” and “Their Mentor” layers is characterized by a pronounced divergence, signifying fewer shared characteristics, possibly stemming from the differing social connotations associated with declaring or acknowledging a mentoring relationship.

The “Joint Publication” layer diverges considerably from the majority of other layers, as denoted by its darker red coloration, underscoring its unique position within the network. Contrastingly, the “Professional Advice” layer manifests low divergence with the “University Business” layer, yet high divergence with the “Conference” and “Joint Publication” layers, suggesting alignment with institutional business practices

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<sup>1</sup>The dendrogram in Appendix G also illustrates the hierarchical clustering of Team J’s Professional network layers, revealing the relative JSD values that guide the aggregation process.



**Figure 5.3: Heatmap and Dendrogram of Jensen-Shannon Divergence for Team J’s Professional Network Layers.** The heatmap’s color coding illustrates the divergence between layers, with a dendrogram that clusters layers by their similarity, providing a guide for network layer aggregation.

over scholarly activities.

The dendrograms, positioned along the axes, cluster the layers according to their similarity, with branches merging at points that reflect the JSD between clusters. The height of the merge point is indicative of the distance, where lower points imply closer similarity. This hierarchical clustering directs the aggregation process, informing the sequence of merging layers to simplify the network’s structure.

The sub-layers are amalgamated sequentially, with the initial aggregation joining the “University Business” and “Professional Advice” sub-layers, owing to their minimal JSD. Subsequent calculations of the JSD identify “Their Mentor” and “Joint Publication” as the next pair with the lowest divergence, leading to their combination. This iterative process continues, with the JSD recalculated after each aggregation. The ensuing step observes “My Mentor” and the first aggregated unit—now designated as “Aggregation 1,” the fusion of “University Business” and “Professional

Advice”—as possessing the smallest divergence, prompting their unification. This amalgamation, henceforth referred to as “Aggregation 2,” is then analyzed further. “Grant Proposal” and “Aggregation 2” are then merged due to the lowest divergence, resulting in “Aggregation 3.” As the process advances, “Conference” and “Aggregation 3” (encompassing “My Mentor,” “University Business,” and “Professional Advice”) present the lowest JSD, forming “Aggregation 4.” The second to last aggregation involves “Aggregation 4” and the previously combined “Their Mentor” and “Joint Publication,” termed “Aggregation 2.” The final aggregation is the complete “Professional” multilayer network.<sup>2</sup>

Following each aggregation, the mean relative entropy, specifically the Von Neumann entropy ( $q(\lambda)$ ), is computed to illustrate the informational change at each step. This progression of aggregations and entropy calculations culminates in a plot that elucidates the hierarchical structure and similarity relationships within the network.

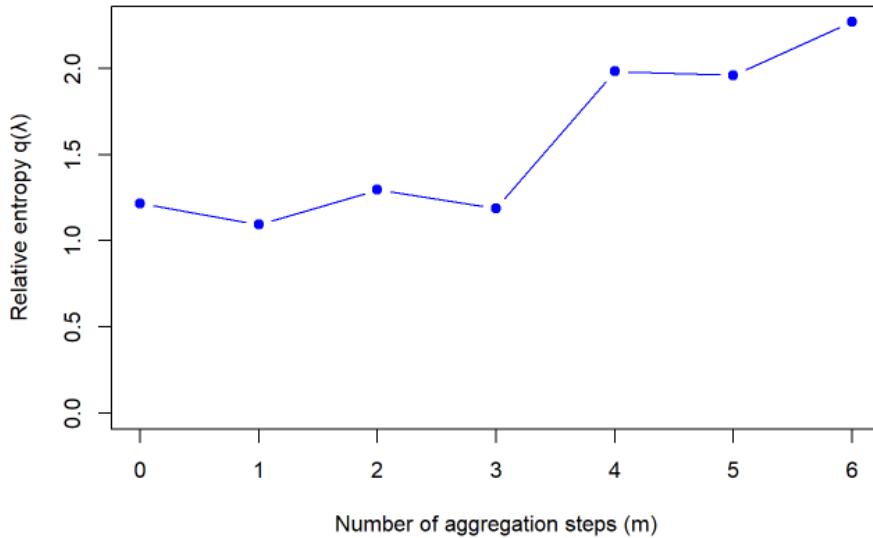
Figure 5.4 traces the trajectory of relative entropy through consecutive stages of layer aggregation in the “Professional” network. The  $q(\lambda)$  of the original, unconsolidated network is set as a baseline at  $m = 0$ . Each subsequent point, from 1 to 6, corresponds to an aggregation step, with point 6 representing the culmination of the process where all layers are fully merged.<sup>3</sup>

At the outset, with no layers combined, the average  $q(\lambda)$  stands at 1.2176. Upon the first aggregation, encompassing “University Business” and “Professional Advice,” there is a slight decrease in  $q(\lambda)$  to 1.0931, which could imply that the aggregated layers exhibit some dissimilarity, potentially leading to the introduction of artificial structural patterns as suggested by Domenico *et al.* (2015). The second aggregation,

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<sup>2</sup>The Jensen-Shannon Distance Matrix for each aggregation step is available in Appendix G.

<sup>3</sup>The mean relative entropy values during layer aggregation are displayed in Appendix G.



**Figure 5.4:** Relative entropy progression during the aggregation of the Professional network’s layers. The plot delineates changes in Von Neumann entropy ( $q(\lambda)$ ) from the original network to complete aggregation, highlighting the impact of each aggregation step on network complexity.

unifying “Their Mentor” and “Joint Publication,” sees an increase in entropy to 1.2954, indicative of a reduction in redundancy within the network’s structure.

The third step of aggregation merges “My Mentor” with “Aggregation 1,” yielding an entropy of 1.1862. The reduction in entropy may suggest that “My Mentor” and “Aggregation 1” are dissimilar, and thus their aggregation could be less than ideal from a statistical standpoint. The fourth aggregation introduces “Grant Proposal” to “Aggregation 3,” resulting in a decreased entropy of 0.9668. A subsequent rise in entropy after this step indicates a potential reduction in redundancy, which might justify this aggregation’s utility in multilayer network analysis.

The addition of “Conference” edges to “Aggregation 4” in the fifth step brings about a significant increase in entropy to 1.4392, suggesting a lack of artificial structural patterns due to the similarity of these networks. Finally, the complete aggregation of the Professional network reflects a substantial elevation in entropy to 2.2017,

signifying a marked change and emphasizing the complex, multi-faceted nature of the aggregated network.

The analysis of relative entropy in the context of layer aggregation within multi-layer networks illuminates the structural dynamics of such systems. An elevation in the mean relative entropy ( $q(\lambda)$ ), as posited by (Domenico *et al.*, 2015), generally signifies either the confluence of layers that preserve sub-additivity or the coalescence of layers with closely aligned structures. The maximization of  $q(\lambda)$  serves as a strategic approach to eschew configurations laden with spurious structures or redundant layers (Domenico *et al.*, 2015). A decrease in  $q(\lambda)$ , conversely, often indicates an aggregation that may be less than ideal, particularly if it integrates layers with disparate edge densities or engenders structural patterns absent in the original layers (Domenico *et al.*, 2015).

The observed entropy dynamics across the aggregation steps—from aggregation 0 to aggregation 6 show an initial dip in entropy upon merging “University Business” and “Professional Advice” suggests a potential introduction of artificial structural patterns. However, subsequent increments, particularly from aggregation 1 to aggregation 2 and then in the final step to aggregation, point to successful reductions in redundancy, aligning with the principles of desirable aggregation.

**Layer Aggregation Discussion** The aggregation sequence of the multilayer networks within the ‘Professional’ multilayered network offers a nuanced view of the relationships and their hierarchical significance. The initial combination of “University Business” and “Professional Advice” suggests a foundational connection between administrative duties and the dissemination of expertise, reflecting the relationship within institutional practices.

The subsequent aggregation of “Their Mentor” and “Joint Publication” layers, although seemingly disparate, may indicate an underlying pattern of knowledge dissemination where mentorship influences scholarly output, albeit this linkage is not as pronounced as other couplings within the network. This combination, followed by the merger with “My Mentor,” signals a divergence from the expected pattern where mentorship roles would align more closely with professional guidance rather than publication activities.

Notably, the “Grant Proposal” layer, which logically aligns with “Joint Publication” due to the progression from research funding to output, does not merge until later in the sequence, suggesting a more complex relationship than initially hypothesized. This later-stage merger could imply that while grant proposals are instrumental in research production, the pathway from funding to publication is not as direct and is perhaps mediated by other professional interactions.

The final stages of aggregation, which incorporate the “Conference” layer into the mix, underscore the interplay between academic discourse, as represented by conferences, and the combined layers of mentorship and administrative-business advice. The culmination of these layers into a single aggregated network indicates a multi-faceted professional environment where various forms of professional engagement are deeply intertwined.

In light of these observations, the aggregation order not only delineates the structural similarities between layers but also hints at the social processes underpinning professional interactions. The depth of coupling between specific network layers, such as mentorship and its professional advice components, versus the broader scholarly activities reflected in publications and conference engagements, unravels the fabric

of professional networks in an academic setting. The resulting structure, as revealed by this aggregation sequence, provides a scaffold upon which the complexities of academic-professional relationships can be understood and further explored. This methodical approach to understanding professional interactions sets the stage for a parallel analysis of the ‘Personal’ network, promising to yield comparative insights into the social dimensions of the research community.

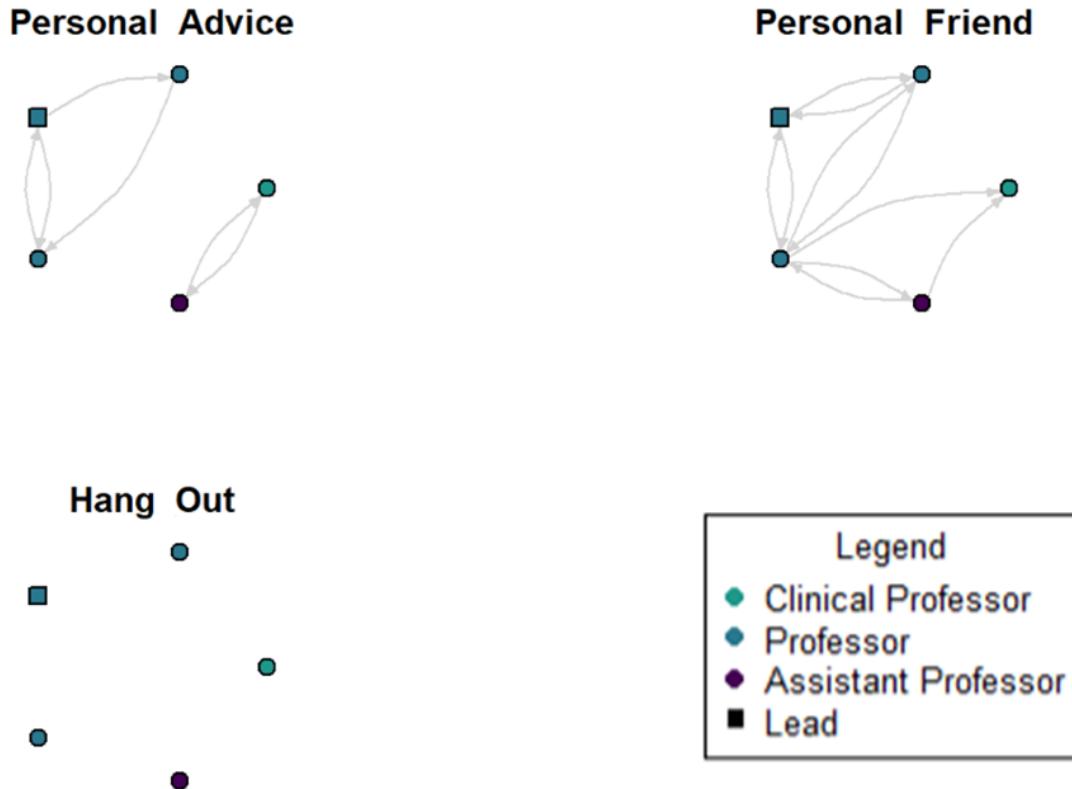
### **Personal Network**

The “Personal” multilayered network, comprising single-valued ties, encapsulates the informal social interactions among Team J members, manifesting in sub-layers “Personal Advice”, “Hang Out”, and “Personal Friend” networks.

Figure 5.5 visualizes the informal social landscape of Team J, with each node representing an individual and the edges depicting the various personal interactions, whether seeking advice, forming friendships, or expressing the desire to socialize outside of professional settings. The “Personal Advice” and “Personal Friend” sub-layers are characterized by visible interactions, while the “Hang Out” sub-layer remains sparse, indicating no instances of socializing intentions being reported or recognized within the team.

This detailed visual representation provides a foundation for understanding the informal social networks that underpin the formal professional structures, thus offering a comprehensive view of the team’s dynamics. Subsequent analysis will extend this exploration to delineate the patterns and implications of these personal networks, analogous to the preceding examination of the professional networks.

As done with the “Professional” networks, the individual network layers are com-



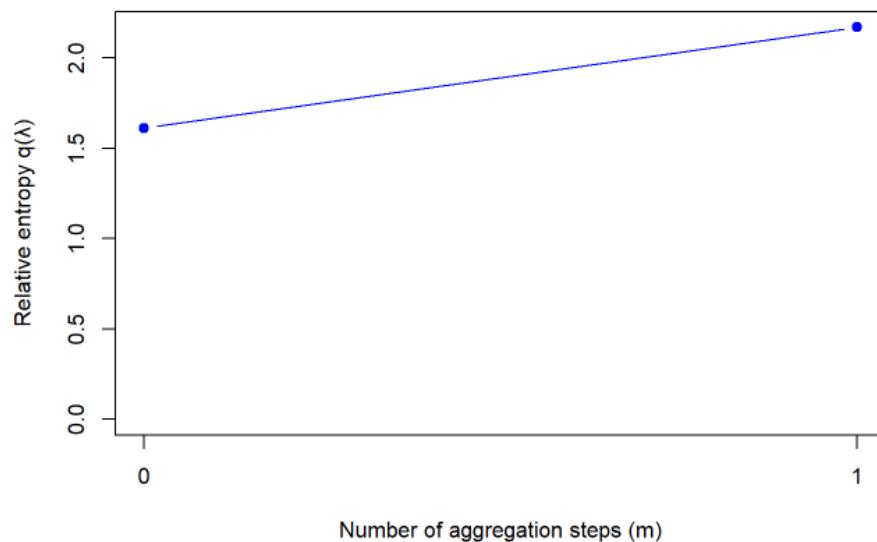
**Figure 5.5: Personal Sub-Layer Networks of Team J:** This figure illustrates the spectrum of informal social engagement within Team J, segmented into sub-layers of personal advice, social gatherings, and friendships. The consistent positioning of participants across sub-layers facilitates a comparative visual analysis. The square node signifies the team lead, and node colors differentiate faculty ranks, as explicated in the legend. Curved edges highlight the directionality of interpersonal connections.

pared for similarity to determine if the aggregation is appropriate for statistical analysis. “Hang out” is excluded as this sub-layer network does not contain edges. The matrix in Table 5.2 displays the Jensen-Shannon distances between “Personal Advice” and “Personal Friend” sub-layers reveals a divergence value of 0.3637. This figure, which is notably low, suggests that the nature of interactions within these two personal networks shares a significant degree of similarity, implying that members who seek personal advice also tend to form personal friendships within the team.

Figure 5.6 presents a clear upward trajectory in relative entropy during the singu-

| Personal Advice | Personal Friend |
|-----------------|-----------------|
| 0.3637107       |                 |

**Table 5.2:** Jensen-Shannon Distance Matrix for Personal Sub-layer Networks. The matrix quantifies the divergence between the pairs of network layers, with the smallest non-zero divergence value highlighting the most analogous pair. The Jensen-Shannon Divergence value of 0.3637 is indicative of a low divergence between “Personal Advice” and “Personal Friend”.



**Figure 5.6:** This plot captures the change in relative entropy ( $q(\lambda)$ ) within the Personal network from no aggregation to a complete merger of layers. The increase in entropy highlights the reduction of redundancy, suggesting that the combined layers are coherent in their depiction of personal relationships within the team.

lar aggregation step of the Personal network layers. This singular point of data reflects a transition from unaggregated individual layers to a fully consolidated network, as indicated by the increase in Von Neumann entropy ( $q(\lambda)$ ).

The relative entropy measurement delineates the consolidation of the Personal network’s layers. The graph indicates an increase in ( $q(\lambda)$ ). from the initial state of separation to the final state of full aggregation. This increment signifies the reduction of redundancy and supports the hypothesis that the “Personal Advice” and “Personal Friend” layers are sufficiently similar to warrant amalgamation without introducing

artificial structural patterns, thereby satisfying the criteria for a favorable aggregation as per the established guidelines.

**Conclusion** The analytical journey through the layer aggregations of both Professional and Personal networks within Team J has illuminated the relationships that underpin the academic dynamic of this team at the beginning of its inception. The aggregation of professional layers, from “University Business” to “Grant Proposals,” and the singular aggregation in the personal layers, between “Personal Advice” and “Personal Friend,” both exhibit an increase in relative entropy—indicative of a successful reduction in redundancy and alignment with the network’s authentic structure. This exploratory analysis has set the stage to transition towards assessing the transformative potential of the GCs initiative. The forthcoming evaluation will find the previous interactions related to scientific productivity and bolster team resilience. By examining the GCs initiative’s impact, the analysis will shed light on the broader implications of structured interdisciplinary collaborations and mentorship dynamics for fostering a vibrant and resilient research community at Boise State.

### 5.5.2 Scientific Productivity

Collaborative activities such as grant proposals and publications quantify creative work production. Leveraging the LOVE survey data, this study scans the pre-existing professional interactions encapsulated in networks of grant proposals and university business involvements to assess the baseline creative output of the case study team. The outlined methodology maps the methods for future analysis to monitor changes to gauge the evolution of team productivity. Concurrently, this thesis uses the “Understanding How” network as a predictive indicator of future productivity. This inquiry into scientific productivity segues into an evaluation of team resilience, exploring how

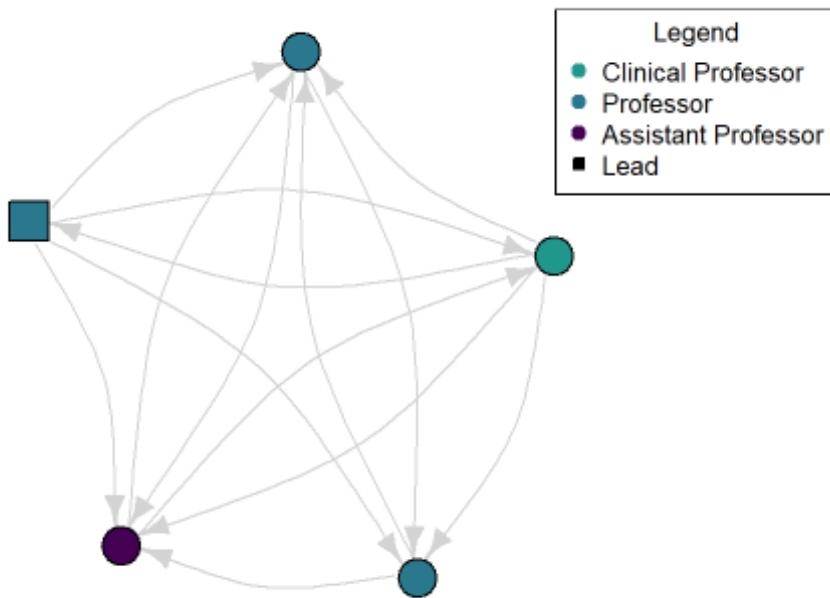
the GCs initiative contributes to developing durable and flexible research collectives, thus framing a holistic view of collaborative success at Boise State.

## Professional Networks

This analytical gateway into the structural aspects of collaborative engagement within the GCs teams offers a granular view of the “University Business” and “Grant Proposals” networks, each a testament to the diverse professional interactions that characterize the academic collective. While the “Joint Publications,” “Conferences,” and “Committee” networks would typically form part of this analysis, it is omitted in the case of the study team due to the low number or absence of edges. The ensuing pages present visualizations of each professional network, accompanied by key network metrics such as density and average degree, which are instrumental in quantifying the intensity and breadth of collaborative ties. These metrics not only reflect the current state of professional interaction within the team but also set a benchmark for tracking the evolution of collaborative patterns over time. Highlighting the critical administrative engagements within Team J, the scientific productivity analysis begins with a concentrated analysis of the “University Business” network.

### University Business Network

Figure 5.7 illustrates the “University Business” network of Team J, showcasing the pattern of administrative collaborations among team members. The strategic placement of nodes allows for an immediate visual comparison of interactions. The square node highlights the team lead, pivotal in the network, while the varied colors of the other nodes signify distinct faculty ranks, aiding in the quick identification of hierarchical structures. The directional edges, curved for clarity, underscore the paths of



**Figure 5.7: Team J “University Business” Network Visualization:** This figure maps the directional flow of university business interactions. The layout positions participants for comparative visual analysis, with the square node identifying the team lead. Node coloration reflects faculty position, as explained in the legend, and curved edges represent the directionality of the interactions, highlighting the flow of engagement in university business matters.

communication and coordination efforts, revealing the network’s flow and the central figures within this professional landscape. The visual representation in Figure 5.7 is quantitatively substantiated by the centrality metrics in Table 5.4, where the extent of each member’s involvement in university affairs is numerically articulated.

A high Total Degree centrality, as seen with Professor 1 and Professor 3, each with a score of 4, implies their extensive engagement in university-related tasks, signaling a broad understanding among team members.

Professor 1 and Professor 3’s significant In-Degree centrality suggests that their role and contributions to university business are widely recognized by the team. Conversely, Clinical Professor 1 and Professor 2, despite a lower Total Degree, have a high Out-Degree of 4, reflecting a non-concordance in reporting university business activi-

|                       | Total Degree | In Degree | Out Degree | Betweenness | Eigenvector |
|-----------------------|--------------|-----------|------------|-------------|-------------|
| Clinical_Professor 1  | 1            | 1         | 4          | 0.0         | -0.610      |
| Professor 1           | 4            | 4         | 2          | 4.0         | -0.357      |
| Professor * 2         | 2            | 2         | 4          | 3.5         | -0.610      |
| Professor 3           | 4            | 4         | 2          | 0.5         | -0.253      |
| Assistant_Professor 1 | 3            | 3         | 2          | 0.0         | -0.253      |

**Table 5.3:** Node-level Centrality Measures for Team J’s “University Business” Network: This table details the distribution of centrality across members, highlighting the individual contributions and roles within the network. It includes measures of Total Degree, In Degree, Out Degree, Betweenness, and Eigenvector centrality, offering a comprehensive view of each member’s involvement in university business activities. The centrality metrics reveal the network’s structure, pinpointing key players and their connectivity, which is essential for understanding the dynamics of collaborative engagement in administrative tasks.

ties. Their proactive stance in reporting interactions may be useful in understanding the reciprocity in these relationships (Ready & Power, 2021).

Betweenness centrality is larger for Professor 1 and Professor 2, with scores of 4 and 3.5, respectively. This result suggests that they often act as bridges or links in the collaborative network of university business, potentially connecting different clusters within the team. Their roles may involve coordinating and facilitating administrative activities across various team members, indicating their strategic positions in the network.

The Eigenvector centrality values, while negative, shed light on the nature of collaborative influence within the team, suggesting an environment where individual autonomy in university business prevails over hierarchical influence. In this context, the negative values may be indicative of a network where individuals are not clustered around a central authority or a group of influencers but are instead likely to engage in university business independently. This independence could reflect a decentralized approach to academic administration within the team, with each member potentially

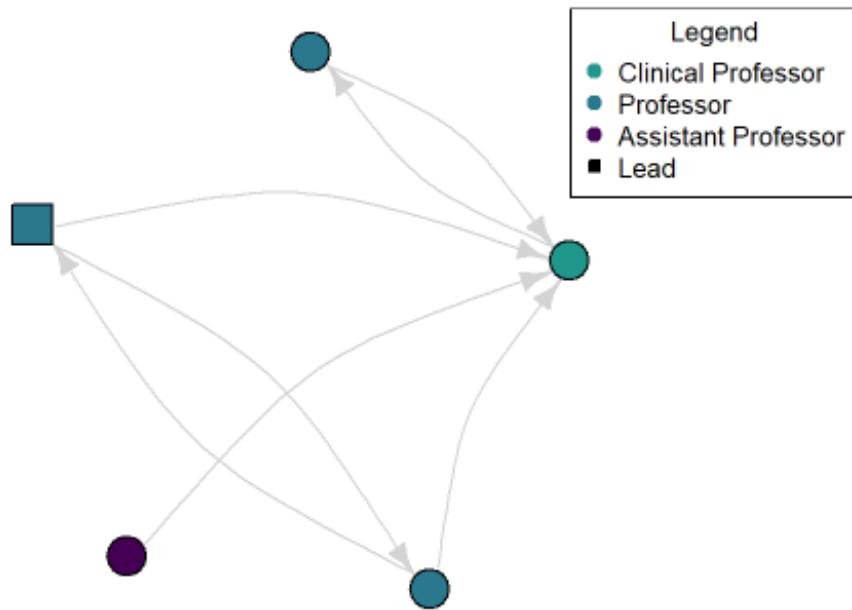
influencing different spheres of the university's operations.

|                       | Total Degree | In Degree | Out Degree | Betweenness | Eigenvector |
|-----------------------|--------------|-----------|------------|-------------|-------------|
| Clinical_Professor 1  | 1            | 1         | 4          | 0.0         | -0.610      |
| Professor 1           | 4            | 4         | 2          | 4.0         | -0.357      |
| Professor * 2         | 2            | 2         | 4          | 3.5         | -0.610      |
| Professor 3           | 4            | 4         | 2          | 0.5         | -0.253      |
| Assistant_Professor 1 | 3            | 3         | 2          | 0.0         | -0.253      |

**Table 5.4: Network Metrics for Team J’s “University Business” Network:** This table outlines crucial network metrics pre-treatment, including degrees and density, to assess the collaborative landscape of university business activities within Team J. With a notable density of 0.7, the table provides a quantitative snapshot of the network’s connectivity prior to any interventions.

In the “University Business” network of Team J (Table 5.4, a network density of 0.7 signifies a high level of connectivity among team members in their administrative and operational collaborations. In simpler terms, 70% of all possible collaborative connections that could exist in the network are actually realized. This high density indicates that team members are extensively involved with each other in university business matters, suggesting a cohesive group with strong collaborative ties. Such a dense network is indicative of a productive environment where members are likely to share responsibilities, resources, and information efficiently. Monitoring this density over time will enable the SNAP project to identify changes in the team’s collaborative patterns, offering insights into the evolution of their professional interactions and the potential impact of the GCs initiative on fostering an integrated academic community. The current high network density is a promising indicator of Team J’s administrative health, serving as a baseline against which future changes in team dynamics can be measured, particularly in response to the GCs initiative. The attention now shifts to the realm of research funding within the “Grant Proposals” network.

### Grant Proposals Network



**Figure 5.8: Team J “Grant Proposals” Network Visualization:** This figure highlights the level of agreement or consistency in reporting prior co-proposing interactions within the team. The square node represents the team lead, with other nodes differentiated by color to indicate faculty position in accordance with the legend. The arrowed edges trace the concordance in identifying prior collaborative grant-writing efforts among team members.

In Figure 5.8, the “Grant Proposals” network of Team J is depicted, showing the interconnections among team members in the context of grant application processes. The visualization places the team lead as a distinct square node, indicative of their central role in grant initiatives. The nodes, color-coded by academic rank, allow for the identification of the faculty hierarchy and are linked by arrows that specify the initiator of the collaborative effort. This directional mapping provides a clear representation of the grant proposal dynamics, identifying which members are actively engaging others in the pursuit of research funding. The visual cues in the figure are quantitatively grounded in the centrality metrics provided by Table 5.5.

|                       | Total Degree | In Degree | Out Degree | Betweenness | Eigenvector |
|-----------------------|--------------|-----------|------------|-------------|-------------|
| Clinical_Professor 1  | 1            | 1         | 2          | 0           | 0.707       |
| Professor 1           | 0            | 0         | 1          | 0           | 0.000       |
| Professor * 2         | 4            | 4         | 1          | 3           | 0.000       |
| Professor 3           | 1            | 1         | 1          | 0           | 0.000       |
| Assistant_Professor 1 | 1            | 1         | 2          | 0           | 0.707       |

**Table 5.5:** Node-level Centrality Measures for Team J’s “Grant Proposal” Network: This table details the distribution of centrality across members, highlighting Professor 2’s prominent role in grant-related collaborations. An asterisk marks the team leader, accentuating their role in the network. The data indicates a network with selective collaborative engagement in grant proposals rather than uniform activity across all members.

This table presents network metrics for each individual. The Total Degree centrality in this network reflects the number of collaborative connections each individual has regarding co-authoring grant proposals. Clinical Professor 1 and Assistant Professor 1, each with a Total Degree of 1, have been involved in a grant proposal with one other team member, indicating limited collaborative engagement in grant-seeking activities. Professor 2, marked with an asterisk to denote their leadership role, has a Total Degree of 4, suggesting they are the most collaboratively active in grant proposal efforts, having worked with every other member of the team. These centrality measures paint a detailed picture of the team’s grant proposal efforts, indicating potential areas for increased collaborative engagement and leadership.

In-Degree centrality for Professor 2 is also at 4, which means all other team members have engaged with them in grant proposal activities. This value highlights Professor 2’s central role in grant collaborations and their expertise or leadership in navigating the grant application process. The zeros for Professor 1 and the low scores for Professors 3 and Assistant Professor 1 suggest that these individuals need to be more central to grant proposal collaborations within the team.

Out-Degree centrality varies, with Clinical Professor 1 and Assistant Professor 1 each showing an Out-Degree of 2 despite their low Total Degree. This number indicates that while they may not be involved in many grant proposals, they are proactive in reaching out to collaborate when they engage in grant-seeking. Professor 2 has an Out-Degree of 1, which, combined with their high In-Degree, suggests that while they are frequently sought for collaboration, they are selective in initiating grant proposals.

Betweenness centrality is solely non-zero for Professor 2, with a score of 3, pointing to their unique position as a mediator in the collaboration flow. This result suggests that Professor 2 plays a pivotal role in connecting team members on grant proposals, possibly bridging gaps between otherwise unconnected pairs or groups within the team.

Eigenvector centrality scores are high for Clinical Professor 1 and Assistant Professor 1 and near zero for others, indicating that while the former two may not be central in terms of the quantity of collaborative ties, they are significant in terms of the structural importance of their connections. Their high Eigenvector scores could suggest that their few collaborations are with highly central or influential team members, possibly Professor 2, given their leadership and central role in the network.

The “Grant Proposal” network of Team J, as presented in Table 5.6, reveals a network density of 0.1. In plain terms, density measures the proportion of actual connections in a network relative to all possible connections. For Team J, this density indicates that, out of all possible pairings between members for grant collaborations, 10% are actualized. While this metric does not categorize the density as high or low in isolation, it establishes a foundational reference for future comparative analysis.

|                        | Pre-treatment |
|------------------------|---------------|
| Mean Total Degree      | 1.4           |
| Mean Out Degree        | 1.4           |
| Network Size           | 5             |
| Edges                  | 7             |
| Dyads Possible         | 20            |
| Density                | 0.3           |
| Component Count        | 1             |
| Largest Component Size | 4             |
| Connectedness          | 1             |

**Table 5.6: Whole Network Measures for Team J’s “Grant Proposal” Network:** This table enumerates key indicators of the network’s structure, including mean degree and density, offering insights into the collaborative history of grant proposal activities among team members. A density of 0.1, without comparison to other networks, serves as a baseline measure of connectivity among team members in this context.

Observing how this density metric changes over time will be crucial in understanding the development of collaborative tendencies among team members, particularly how they may evolve to create a more closely knit network indicative of increased scientific productivity. The current network density serves as a benchmark for Team J, setting the stage for longitudinal analysis to observe how collaborative engagement might intensify and support the team’s collective scientific productivity.

**Professional Networks Discussion** The analysis of Team J’s “University Business” and “Grant Proposal” networks reveals a nuanced landscape of professional interactions, highlighting both the collaborative strengths and areas for growth within the team. The “University Business” network showcases a high degree of collaboration and mutual recognition among members, particularly Professor 1 and Professor 3, indicating a robust framework for university-related activities. In contrast, the “Grant Proposal” network illustrates a more selective pattern of engagement, with

Professor 2 playing a central role in collaborations. Despite its lower density, this network offers insight into the potential for enhancing grant-seeking activities. These findings, set against the backdrop of the team's pre-formation creative work, provide a baseline for future analyses. By monitoring changes in the Professional networks' density and average degree, the CRCA aims to track the evolution of each Team's productivity, using these metrics as benchmarks for assessing scientific productivity and the impact of the GCs initiative on fostering a collaborative and dynamic research environment. This approach underscores the importance of understanding and enhancing the interconnectedness and collaborative efforts within research teams. This foundational analysis of current professional networks within Team J sets the stage for a deeper historical examination of grant proposal activities, which will provide additional context to the team's collaborative culture.

### **Grant Proposal Experience**

Expanding upon the intricate network of current professional interactions within Team J, the subsequent analysis ventures into a historical examination of the team's grant proposal endeavors. Distinct from the internally focused "Grant Proposals" network derived from recent survey data, this section casts a wider net, reviewing collaborative grant proposals penned alongside any Boise State faculty from 2016 to 2020. This retrospective probe is crucial, as it unveils the depth and breadth of each member's engagement in research funding pursuits. By exploring these historical ties, the analysis aims to illuminate the team's collective experience and potential in grant acquisition, offering a comprehensive view of their scientific enterprise prior to the formation of the team and the implementation of the GCs initiative.

| Lead  | Position            | PI    | Degree | Betweenness | Proposal Count | Proposal Quartile |
|-------|---------------------|-------|--------|-------------|----------------|-------------------|
| FALSE | Clinical Professor  | FALSE | 0      | 0.0         | NA             | NA                |
| FALSE | Professor 1         | TRUE  | 4      | 368.0       | 2              | 2                 |
| TRUE  | Professor 2         | TRUE  | 13     | 1742.4      | 8              | 4                 |
| FALSE | Professor 3         | TRUE  | 1      | 0.0         | 1              | 1                 |
| FALSE | Assistant Professor | TRUE  | 3      | 0.0         | 2              | 2                 |

**Table 5.7: Team J’s History of Grant Co-Proposing:** This table delineates Team J’s grant proposal history from 2016 to 2020, detailing roles, collaboration breadth, and influence within Boise State’s research community. It includes members’ roles as principal investigators (PI), their collaborative network degree, betweenness centrality, total count of grant proposals, and their distribution across quartiles of proposal activity.

Table 5.7 presents a comprehensive view of Team J’s grant proposal history at Boise State, incorporating metrics that delineate the breadth and depth of each team member’s involvement in research funding efforts. The ‘Degree’ metric showcases the extent of collaborative interactions, with Professor 2, the team lead, exhibiting a high Degree centrality of 13, indicative of their broad engagement and central role in the grant-seeking process. Their Betweenness centrality of 1742.4 further underscores their influence as a connector among various members of the research community. This central involvement is complemented by the highest Proposal Count of 8, situating Professor 2 in the top quartile of proposal activity and underscoring their potential as a mentor for grant-writing within the team.

Professor 1 and the Assistant Professor demonstrate a strong, albeit less extensive, involvement in grant proposals, as reflected by their respective Degree centralities and second-quartile rankings, suggesting that they are integral to the team’s grant-seeking initiatives. The balance in their In-Degree and Out-Degree centrality indicates a mutual engagement in collaborations, pointing to a dynamic participation in the grant application landscape.

In stark contrast, Professor 3, while a principal investigator, shows limited engagement with a Degree centrality of 1 and minimal Betweenness centrality, suggesting a targeted or specialized approach to grant-seeking. The Clinical Professor's non-participation in the grant network could indicate a recent association with Boise State or a concentration on alternate academic responsibilities. If the former, membership in the team presents as an avenue for development, possibly through increased interaction with more active grant-writing members.

**Proposing Experience Discussion** The metrics from the Grant Co-Proposing table, particularly the variation in members' involvement and influence in grant proposals, provide actionable insights into the team's collective experience. It highlights the need for strategic mentorship and the potential benefits of fostering a more balanced distribution of grant-writing expertise across the team, aligning with the overarching goals of the GCs initiative to enhance collaborative research efforts at Boise State University.

The disparity in grant proposal activity, particularly the Clinical Professor's absence, underscores an opportunity for mentorship—an integral component of the GCs initiative aimed at fostering a fair and collaborative research culture. As Norton *et al.* (2017) emphasize, mentorship by well-connected members can significantly enhance collaborative efforts. The Clinical Professor's absence of grant proposal activity within the observed period may signify them as a new entrant to Boise State, or they may have been focusing on other academic duties. If the former, membership in the team presents as an avenue for development, possibly through increased interaction with more active grant-writing members. Leveraging the mentorship model could not only address this gap but also align with Boise State's strategic goal of enhanc-

ing educational access, fostering a culture of mutual growth, and transforming team dynamics for increased scientific productivity.

|                                   | Team J in CUPID 5-Year | Whole 5-Year Network Stats |
|-----------------------------------|------------------------|----------------------------|
| Members                           | 5                      | 557.0                      |
| Grant Network Proposal (%)        | 80                     | 66.4                       |
| Grant Network PI (%)              | 80                     | 47.8                       |
| Grant Network Mean Degree         | 4.2                    | 4.6                        |
| Grant Network Mean Betweenness    | 422.1                  | 374.5                      |
| Grant Network Mean Proposal Count | 3.2                    | 4.3                        |

**Table 5.8: Team J’s CUPID 5-Year Grant Proposal Network Metrics:** This table contrasts Team J’s grant proposal engagement and leadership roles with the broader Boise State faculty over a five-year period, highlighting the team’s relative experience and activity in research funding efforts.

Table 5.8 quantifies Team J’s engagement in the grant proposal process compared to the wider Boise State faculty from 2016 to 2020. The table indicates that 80% of Team J members were involved in collaborative grant proposals, surpassing the university-wide collaboration rate of 66.4%. This suggests a high propensity among Team J members to engage in joint research funding endeavors. Similarly, the PI percentage for Team J stands at 80%, meaning that each member who collaborated on a grant also served as a Principal Investigator at some point, underscoring a notable level of leadership and experience in managing research projects compared to 47.8% across the wider faculty network.

The mean degree of 4.2 for Team J reflects the average number of collaborative connections per member in grant proposals, which is slightly lower than the overall network’s mean degree of 4.6. This measure indicates an active but not the most central role in the larger grant-seeking community. The mean betweenness centrality of 422.1 for Team J, higher than the network average, suggests that team members frequently serve as vital links in the flow of collaboration, potentially integrating

diverse research interests and disciplines.

The mean proposal count of 3.2 signifies the average number of grant proposals per member in Team J, which is marginally less than the broader faculty's average, indicating that while Team J is active in submitting proposals, there is room to increase their output to match or exceed the broader faculty benchmark. This metric, along with the collaborative and leadership percentages, paints a picture of a team well-versed in the grant proposal process yet with the potential for further growth by broadening its membership to include emerging scholars, thereby enhancing mentorship opportunities and diversifying the team's collaborative strength.

**Grant Proposals Network Discussion** Team J's prowess in crafting grant proposals is highlighted by its members' substantial history of leadership in this crucial academic endeavor. This collective proficiency, however, does not overshadow the potential for experience diversity, which thoughtfully combines both seasoned scholars and emerging talents. Such a blend fosters an environment ripe for mentorship, where knowledge exchange and collaborative learning are paramount. Diversity in experience enhances a team's capacity for mentorship. This diversity is instrumental in creating a nurturing environment that promises not only to elevate Team J's success in securing grants but also to bolster the collective research acumen of its members. This synergy of experience and emerging talent sets a robust foundation for Team J's continued excellence and innovation in research funding endeavors.

Building on the insights gleaned from Team J's grant proposal dynamics, the next figure for analysis expands to encompass a broader perspective, examining the network of grant proposal collaborations across the GCs teams and their extended network. This wider lens aims to uncover the structural patterns of co-proposing

experience and mentorship opportunities that pervade the entire GCs research community beyond the confines of individual teams.

Figure 5.9 selectively delineates the collaborative grant proposal patterns among members of the GCs teams and their collaborators at Boise State University. In this refined visualization, square nodes of all sizes are observed, indicating a spectrum of experience among the GCs team members and their grant-proposing collaborators. The presence of larger squares suggests that there are highly experienced members within the GCs teams who have a history of frequently collaborating on grant proposals. The large cluster at the bottom points to a potential pattern of cumulative advantage. However, the overlay of somewhat smaller nodes in close proximity to these larger squares suggests a pattern of mentorship. It appears that the node size for this sub-network is generally larger.

Expanding further, Figure 5.10 extends this scope to encompass the entire spectrum of collaborative grant proposal activities within Boise State University over the last five years. This broader perspective aims to capture the full expanse of research funding interactions, highlighting the role of GCs team members within the wider university context and illustrating the extensive network of faculty engaged in collaborative grant-seeking endeavors.

Figure 5.10 portrays the degree centrality within Boise State University's five-year grant proposal network, using node size and color gradient to represent the degree of connectivity among researchers. The node size escalates from small to large, while the color spectrum transitions from blue to red to signify an increasing degree centrality; smaller, blue nodes indicate researchers with fewer collaborative ties, while larger, red nodes represent those with a higher frequency of co-authored grant proposals.

Central to the network is a dense agglomeration of large, red, and purple nodes, which suggests a pattern of cumulative advantage. This term refers to the phenomenon where well-recognized scientists tend to collaborate preferentially with other established peers, as proposed by (Mali *et al.*, 2012). This concentration of collaborations among highly connected individuals or “hubs” hints at a scale-free structure, potentially indicative of a hierarchical network. Such a configuration may be reflective of existing disparities in resource allocation and collaborative opportunities within the research community, as it suggests that established researchers might be accumulating more resources and recognition.

On the periphery of this central cluster, one can observe smaller, blue nodes extending outward and connected to larger nodes. This arrangement could represent a mentorship dynamic, where more experienced researchers (large red nodes) are

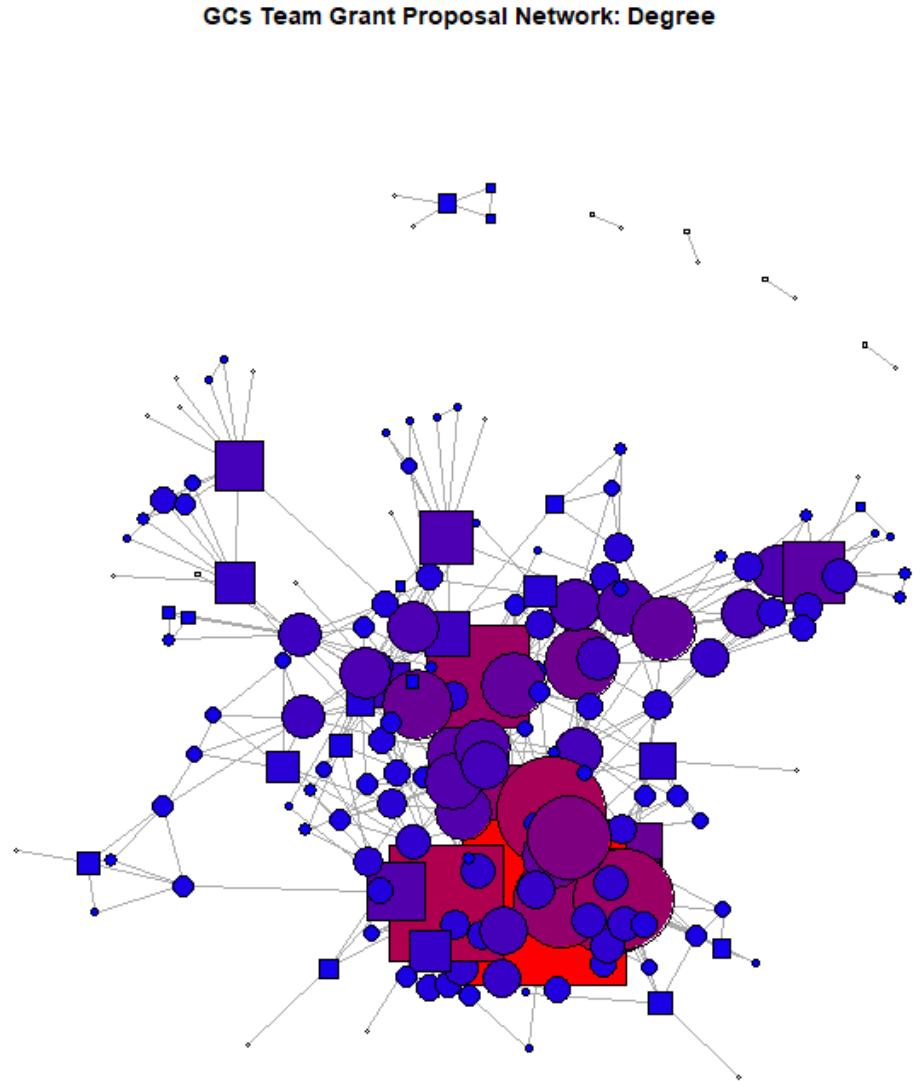


Figure 5.9: Network visualization of GCs team members and their 5-year historical grant proposal collaborations (CUPID). Square nodes represent GCs team members, and circular nodes represent their collaborators. Node size and color indicate the degree, with larger, redder nodes indicating more frequent collaboration. The visualization reflects the diversity of experience within the GCs teams, suggesting patterns of both cumulative advantage and mentorship in grant proposal collaborations.

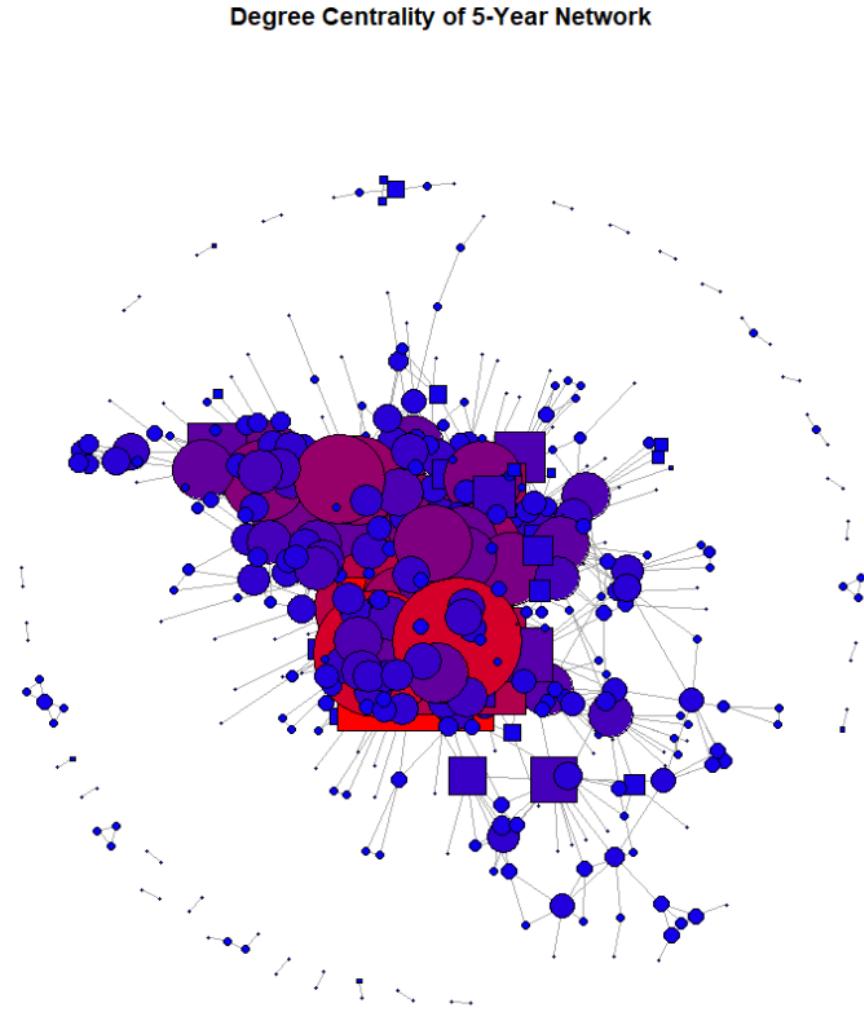


Figure 5.10: Network visualization of all collaborative grant-proposing faculty members between 2016 and 2020. Squared nodes identify GCs team members who are included in the network. The large, red nodes that are connected to other large, brightly colored nodes reflect a concentration of experience and a pattern of cumulative advantage. Large, red nodes connected to smaller, bluer nodes suggest a mentoring relationship of less connected researchers. The patterns observed may also inform institutional strategies to encourage more equitable collaboration and resource sharing, with the aim of nurturing both experienced and early-career researchers within the academic ecosystem.

collaborating with emerging scientists (small blue nodes), possibly facilitating the distribution of knowledge and opportunities.

The visualization also includes square-shaped nodes of varying sizes, denoting members of the Grand Challenges teams. Their distribution across the spectrum from large, red squares to smaller, purple and blue squares, indicates that the GCs teams are composed of a mix of highly experienced researchers as well as rising stars, which could be essential for fostering innovation and ensuring the transfer of expertise within these teams. The presence of diverse degree centralities within the GCs teams suggests a balanced structure that could support both the development of new talent and the leveraging of established researchers' expertise.

### **Understanding How Network**

The Understanding How network of Team J, depicted in Figure 5.11, stands out for its pronounced cohesiveness, characterized by a notable degree of interconnections denoting mutual understanding among members. The veracity of the data underpinning Team J's Understanding How network might have been subject to the influence of extrinsic variables, notably pre-survey strategic planning sessions facilitated by team science experts. Given the association of these preparatory sessions with the CRCA, it raises the potential for interviewer demand effects. Such effects could manifest through a propensity among team members to modulate their survey responses in alignment with anticipated research expectations, thereby necessitating a cautious interpretation of the network data to accurately capture the essence of the team's collaborative dynamics.

The potential non-interdisciplinary nature of Team J warrants further consider-

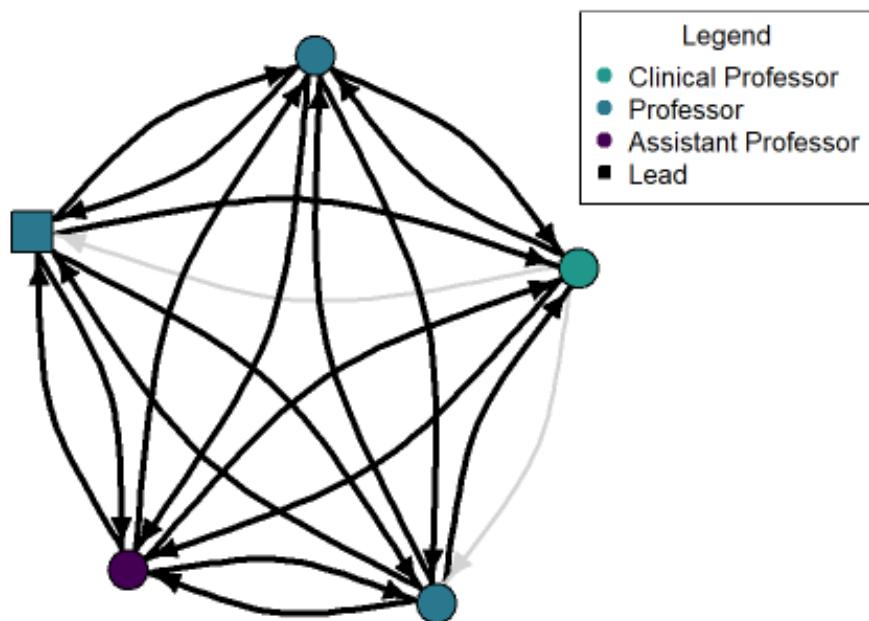


Figure 5.11: The Understanding How network plot shows edge weights become increasingly bolder as the weights become larger. The shape of the lead is square. The colors of the nodes differ by position. The network is completely realized.

ation, especially in light of the network's pronounced cohesiveness. Given the influence of disciplinary backgrounds on mutual understanding within teams, it is conceivable that Team J's significant interconnectedness stems from a higher prevalence of within-discipline relationships. This scenario would naturally facilitate a shared comprehension of how team members' disciplines contribute to the collective effort, potentially skewing the Understanding How network's portrayal of interdisciplinary collaboration.

In concluding that Team J is well-equipped for collaboration, based on their mutual understanding as depicted in the Understanding How network, it is crucial to contextualize this assessment within the broader analysis. The network's high degree of interconnectedness, while indicative of strong collaborative potential, also necessitates a critical evaluation of the underlying factors contributing to this outcome, including the team's disciplinary composition and the mechanisms in place to address potential biases.

**Scientific Productivity Discussion** This thesis investigated scientific productivity in several ways. The focus on their "University Business" and "Grant Proposals", highlights the team's collaborative strengths and areas for growth, with particular attention to the roles of key members in fostering university-related activities and grant-seeking endeavors. The incorporation of historical grant proposal data further enriches the understanding of the team's collective experience and potential for future success in grant acquisition. It emphasizes the importance of mentorship and the integration of diverse experiences within the team, suggesting that such a blend of talents can enhance the team's research capabilities and grant-winning prospects. Additionally, the broader examination of grant proposal collaborations across the GCs

research community aims to identify collaborative patterns and mentorship opportunities, enhancing the research ecosystem's overall capacity. The analysis concludes with an affirmation of Team J's preparedness for collaboration, as evidenced by the Understanding How network, but also calls for a critical evaluation of the factors contributing to a potential bias.

### **5.5.3 Team Resilience**

The resilience of research teams, pivotal to their long-term success and adaptability, forms the focus of this section of the analysis. This subsection delves into the multi-faceted aspects that contribute to the resilience of Team J within the broader context of the GCs initiative at Boise State. The resilience of a team is not merely its capacity to endure but also its ability to evolve, expand, and excel in the face of challenges. To this end, the analysis is structured around several critical components: Department and Position, Mentoring and Advice Networks, Roster Expansion, Knowledge Of network, and Personal Networks. Each of these components plays a vital role in shaping the resilience of the team, reflecting the complexity of building and sustaining effective research collaborations. The analysis begins with an exploration of the structural dimensions of Team J, examining how the diversity of departmental affiliations and the variety of positions within the university contribute to a robust foundation for interdisciplinary collaboration and mentorship.

#### **Department and Position**

This section examines Team J's composition, with a particular focus on the range of experience levels and interdisciplinary breadth within the team. Such an analysis can delineate the impact of departmental affiliations and hierarchical positions on the

team's resilience and innovative capabilities. A diverse team composition incorporates various levels of experience to facilitate mentoring relationships and meets the interdisciplinary prerequisites mandated for future funding opportunities. The aim of tracking team composition changes through time elucidates how the multifaceted composition of a team, encompassing a range of disciplinary backgrounds and professional standings, underpins its ability to navigate and thrive amidst the complexities of interdisciplinary research.

**Department Analysis** The assessment of interdisciplinary distance is a key aspect of this analysis, involving the classification of team membership according to a spectrum of within-discipline, short-distance, and long-distance interactions, following the framework established by Bolger (2021). This includes evaluating the extent of cross-departmental collaboration, which signifies short-distance interdisciplinary efforts, and the integration of external entities such as industry, government, and community stakeholders, indicating long-distance interdisciplinary teaming.

Figure 5.12 displays the number of team members from each department for each year. The x-axis displays the year, and the y-axis displays the number of team members. The bar has several colored chunks displaying the number of team members from any one department. Team J contains two members from the Biology Department, two members from the Art Department, and one member from the Department of Theatre, Film, and Creative Writing department. Together, these departments contribute to the diversity of skills and perspectives in Team J, enhancing the potential for cross-disciplinary collaboration and innovation at Boise State. Because this is the first year, there is only one bar. With each successive year, this plot will increase in the number of bars, allowing the display of team growth along with the diversity of

departments.

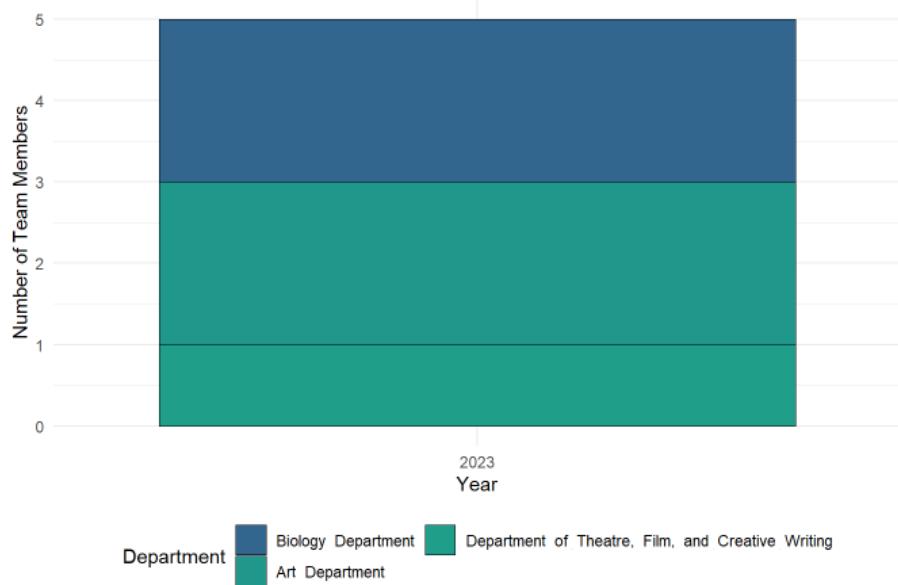


Figure 5.12: Departmental Composition of Team J for 2023. The bar graph illustrates the interdisciplinary mix within the team, with members spanning the Biology, Art, and Theatre, Film, and Creative Writing departments. This demonstrates the team's commitment to embracing diverse academic disciplines, which is integral to the innovative and collaborative environment fostered by the GCs initiative.

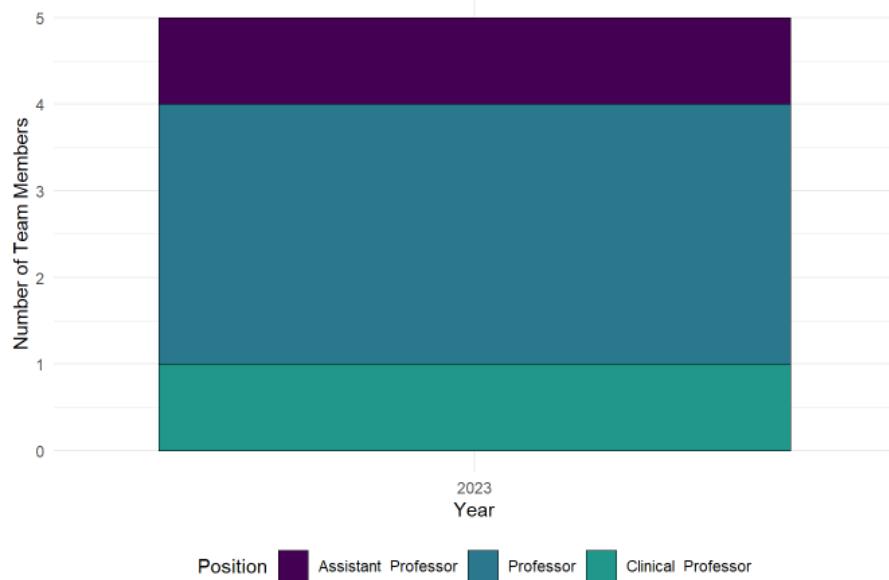
The bar graph in Figure 5.12 presents a visual representation of Team J's departmental composition over time. The x-axis denotes the year, while the y-axis quantifies the number of team members, with distinct colored segments within each bar indicating the contribution of each department. In its inaugural year, Team J comprises two members from the Biology Department, two from the Art Department, and one from the Department of Theatre, Film, and Creative Writing. This diverse assembly of disciplines underscores the team's potential for fostering cross-disciplinary dialogues and generating innovative insights at Boise State. The graphical representation will expand with additional bars in subsequent years, illustrating not only the team's growth but also the evolving diversity of departmental contributions.

**Department Discussion** The bar graph in Figure 5.12 confirms the interdisciplinary constitution of Team J, capturing the essence of the GCs initiative's emphasis on cross-disciplinary collaboration. The presence of team members from the distinct arenas of Biology, Art, and Theatre, Film, and Creative Writing is indicative of a strategic composition that leverages diverse perspectives and expertise. The pronounced cohesiveness Understanding How network, as discussed at the end of section 5.5.2, is not due to the team being comprised of members from the same discipline.

As Team J moves to expand, a strategic approach to interdisciplinary team recruitment can not only enhance interdisciplinary collaboration but also increase the connectedness of Boise State's collaborative networks (Vacca *et al.*, 2015). Targeted network interventions aimed to amplify the university's network connectedness not only enhance the team's capacity for groundbreaking research but also align with Boise State's overarching strategy for fostering a culture of interdisciplinary research and collaboration (Boise State University, 2024).

**Position Analysis** A multifaceted team structure embodies the university's strategic aspirations and exemplifies a model for constructing resilient and adaptive research collectives capable of addressing complex challenges. Student membership and mentorship in the GCs teams encourage these young scholars to become core contributors to scientific productivity, demonstrating the first goal in Boise State's strategy for success (Boise State University, 2024). Concurrently, the presence of faculty across a broad experiential continuum underpins the fourth strategic goal, promoting employee welfare and professional development (Boise State University, 2024).

Figure 5.13 delineates the range of academic positions held by team members and their evolution over time. The x-axis represents the chronological progression, while



**Figure 5.13: Position Composition of Team J for 2023.** The bar graph illustrates the position mix within the team, with members spanning the professors, assistant professor, and clinical professor positions. This demonstrates the team's need to attract mentees.

the y-axis quantifies the constituent members, with color-coded segments within each bar indicating the representation from various faculty ranks. Initially, Team J is composed of three full professors, one assistant professor, and one clinical professor, setting a foundation for robust academic discourse and mentorship.

Anticipating the growth of Team J, strategic inclusion of additional Boise State faculty and students who stand to gain from the tutelage and collaboration with established researchers is imperative. A team that spans the academic hierarchy—from students to full professors—ensures a rich tapestry of research expertise and mentorship opportunities, which are essential for the diffusion of knowledge and support within the collective.

**Position Discussion** The inaugural composition of Team J encapsulates a narrow range of positions, highlighting this team's highly experienced membership. These

members are well-positioned to foster an environment conducive to mentorship and the exchange of scholarly expertise. Experience diversity is crucial for the team's capacity to nurture early-career researchers and integrate them into the new roles of academic productivity. The strategic assembly of team members from different ranks ensures the propagation of knowledge and mentorship, thus serving as a catalyst for collaborative growth and the realization of Boise State's strategic educational objectives.

**Roster Expansion Analysis** The name-generator question within the survey serves as a vital instrument for discerning a team's collaborative tendencies, revealing a preference for either a disciplinary-focused or a transdisciplinary-focused model of collaboration. The responses indicate that Team J has identified 15 individuals as key collaborative contacts. Notably, the majority of these contacts are Boise State faculty (8), predominantly from the Biology department (5), with others representing the Human-Environment Systems (2) and Curriculum, Instruction, and Foundational Studies (1) departments. The identification of these biology department individuals suggests a proclivity for internal, discipline-focused interactions within Boise State. However, the nomination of seven non-faculty individuals points to an inclination towards establishing connections beyond university borders, potentially enriching the team's research with diverse external perspectives from various sectors.

**Roster Expansion Discussion** The strategic growth of Team J should be poised to incorporate a more diverse range of academic experiences in a deliberate effort to foster a robust mentoring environment and interdisciplinary engagement. The team's current composition, all well-established researchers and faculty of Boise State, suggests a strong foundational base across several of the university's academic depart-

ments. The team's identification of individuals outside the faculty—spanning other academic institutions and sectors—demonstrates a commitment to transcending traditional research confines. However, Team J may benefit from network interventions where network analysis identifies specific individuals whose collaboration with the team will improve Boise State's research networks' structural properties (Vacca *et al.*, 2015). This targeted expansion not only fortifies the team's potential for innovative research but also resonates with Boise State's mission to cultivate a dynamic interdisciplinary research culture across campus (Boise State University, 2024). The engagement with a spectrum of individuals, from students to seasoned academics, is expected to catalyze knowledge exchange and mutual support, thereby enhancing the team's resilience and aligning with the university's strategic educational objectives.

**Future Study Limitation** In the context of domain-specific multilayer networks, all participating individuals must be able to engage across the various domains within the combined network, as discussed in Atkisson *et al.* (2020). For example, if a team members cannot co-propose on a grant or co-author a paper, the statistical analysis for a multilayer network should not include this team member in any sub-layer network. Currently, Team J is composed exclusively of Boise State faculty, all of whom can co-propose on a grant or co-author a paper together. However, the forthcoming survey roster is expected to include new team members from external entities such as industry, government, and community stakeholders. This poses SNA methodological challenges that require careful consideration while also investigating the integration of these new team members.

**Transition** The broadening of Team J's roster to include individuals from a spectrum of experiences and disciplines necessitates an examination of the mechanisms

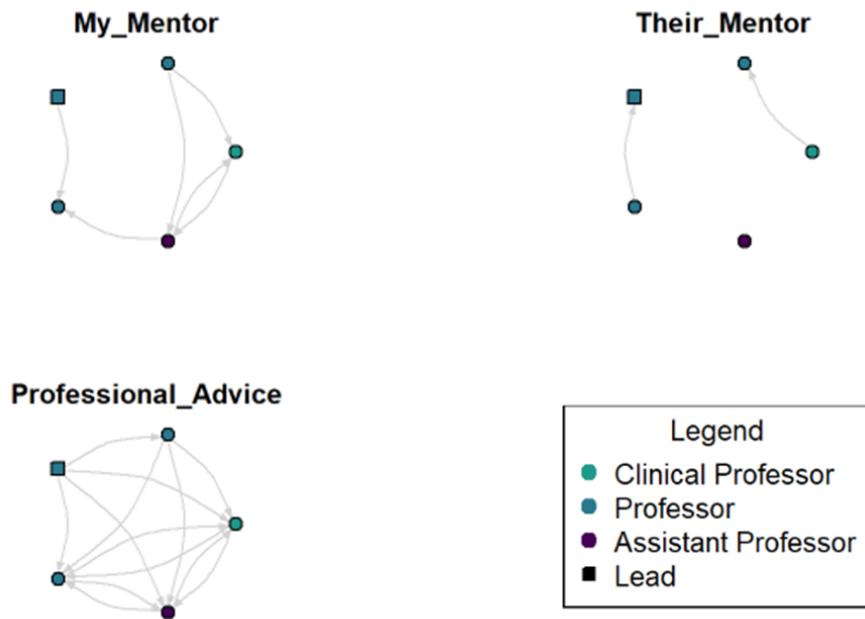
for integrating these diverse perspectives within the existing team framework. Such an examination naturally transitions to an analysis of the Mentoring and Advice Networks, focusing on the critical channels through which knowledge, expertise, and guidance are disseminated among team members, thereby informing the team's collective acumen and capacity for adaptation.

### **Mentoring and Advice Networks**

The professional mentoring and advice networks sheds light on the pre-existing professional relationships that were in place at the inception of the GCs teams and their potential impact on team dynamics. This analysis is the foundation for a longitudinal analysis to investigate how mentorship and advice are associated with the team's collective capacity to navigate interdisciplinary challenges and team membership retention and expansion.

Figure 5.14 displays the identified mentorships and advice-seeking behavior among Team J. In the “My Mentor” network, the Clinical Professor and the Assistant Professor reported receiving mentoring (out-degree of 1 and 2, respectively) yet do not feature as mentors themselves (in-degree = 0). Conversely, Professors 1, 2, and 3 are actively engaged in mentorship, as evidenced by their in-degree of 2, suggesting their integral role in the mentorship structure of the team. This supports the idea that the faculty position is associated with mentoring dynamics.

The “My Mentor” network reflects the perceptions of mentees within the team, while the “Their Mentor” network captures the self-identification of mentors. The sparsity of the “Their Mentor” network may indicate a hesitancy to self-identify as a mentor, which could be attributed to the informality of the mentoring relationship



**Figure 5.14:** Mentoring and Advice Professional Sub-Layer Networks of Team J: The illustration of the “My Mentor,” “Their Mentor,” and “Professional Advice” networks within Team J position team members consistency across the networks to enhance visual comparisons. The team lead is represented by a square node, with node colors reflecting faculty members’ academic ranks according to the legend provided. Directed edges, depicted as curved lines, signify the directionality of mentorship and advice-seeking interactions.

or a lack of recognition for such roles within the team’s operational framework. This phenomenon underscores the potential gap between the receipt of mentorship and the recognition or formalization of the mentor role within interdisciplinary research teams.

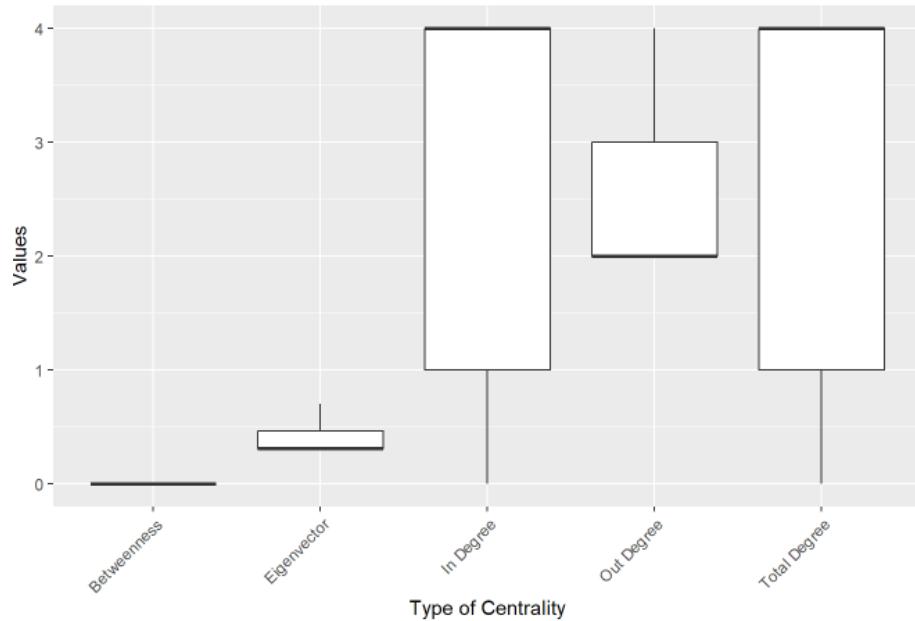
**Mentoring Discussion** The “My Mentor” network’s centrality measures underscore the directional nature of mentoring relationships and reflects the recognition of being a mentee. Yet, the recognition of being a mentor is lacking concordance. The concept of concordance, as described in Ready & Power (2021), refers to the level of agreement or consistency in the reporting of relationships between individuals. It’s a crucial measure in networks where relationships are reported by participants, espe-

cially in cases of “double-sampling” where both members of a dyad report on the same relationship interaction (Ready & Power, 2021). An example of double sampling is the “My Mentor” and “Their Mentor” networks. Concordance can be used to assess the reliability of network data and to understand reciprocity in relationships (Ready & Power, 2021).

If person A nominate B in the “My Mentor” network, B would nominate A in the “Their Mentor” network. Examining the network visualization shows a nonconcordance between “My Mentor” and “Their Mentor” with “Their Mentor” having fewer edges. The overall interpretation of the “Their Mentor” network suggests a limited acknowledgment of mentoring roles within the team, with only a couple of individuals recognizing or being recognized as mentors. This could reflect a reluctance to claim an informal mentorship role, which may be influenced by the team’s culture or professional norms.

In these contexts, indegree represents the number of times an individual is nominated as a mentor or source of advice, indicating their status as a valued mentor within the network. High indegree values signify that a researcher is a pivotal source of guidance and knowledge, embodying the qualities of an experienced and influential mentor. Conversely, outdegree in the “Their Mentor” network reflects the extent to which an individual nominates others as mentees, providing insight into the distribution of mentee-seeking behavior within the team. A higher outdegree indicates active seeking of mentees, highlighting the relational dynamics from the perspective of mentors. Similarly, indegree measures team members’ status as a valued mentee.

**“Professional Advice” Network Analysis** The “Professional Advice” network of Team J, depicted in Figures 5.14 and 5.15, suggests a complex landscape of



**Figure 5.15: Centrality Measures Distribution in the “Professional Advice” Network of Team J:** This box plot visualizes the distribution of centrality measures, offering insights into the dynamics of advice-giving and seeking behaviors among team members. The plot quantifies the direct and indirect roles individuals play in the flow of professional advice, revealing patterns of expertise recognition and knowledge sharing within the team.

knowledge exchange. Table 5.9 shows Professors 1, 2, and 3 emerge as central figures within this network, each with a total degree and in-degree of 4 and out-degree of 2, indicating their significant roles in both giving and receiving professional advice. The Assistant Professor, with a lower total degree, engages less frequently in such exchanges. The high In-Degree centrality for the three professors underscores their status as the primary sources of professional advice, while the Clinical Professor’s high out-degree centrality reflects an assertive stance in seeking knowledge from others. The absence of betweenness centrality across all members points to a non-hierarchical, direct flow of advice within the team. (The network does not have a node that exclusively connects any two other nodes, which explains why betweenness centrality scores are zero.) The Clinical Professor’s notable eigenvector centrality sug-

gests their central role in the network is acknowledged by other key team members, indicating a respected position within the team's professional dynamics. Overall, the network reveals a direct, open channel for advice exchange, with specific individuals playing pivotal roles in disseminating expertise.

|                       | Total Degree | In Degree | Out Degree | Betweenness | Eigenvector |
|-----------------------|--------------|-----------|------------|-------------|-------------|
| Clinical_Professor 1  | 0            | 0         | 4          | 0           | 0.701       |
| Professor 1           | 4            | 4         | 2          | 0           | 0.311       |
| Professor * 2         | 4            | 4         | 2          | 0           | 0.311       |
| Professor 3           | 4            | 4         | 2          | 0           | 0.311       |
| Assistant_Professor 1 | 1            | 1         | 3          | 0           | 0.467       |

**Table 5.9: Centrality Measures in Team J’s “Professional Advice” Network:** This table summarizes the centrality measures derived from Team J’s “Professional Advice” network, ascertaining the dynamics of advice solicitation among team members. The total degree, in-degree, and out-degree columns quantify the involvement of individuals in advisory exchanges. The absence of betweenness centrality values across the board reveals direct interaction patterns, while the Eigenvector centrality scores reflect each member’s influence within this advisory network.

**Mentoring and Advice Networks Discussion** In Team J, mentorship and professional advice appear to be structured around faculty ranks, with full professors serving as the primary nodes of guidance and expertise. The “My Mentor” network reveals that Clinical and Assistant Professors are engaged primarily as mentees and less as mentors, highlighting a possible hierarchical influence on mentorship roles. The notable absence of self-identified mentors in the “Their Mentor” network suggests a potential undervaluation of informal mentoring relationships. Contrastingly, the “Professional Advice” network is more densely populated, with Professors 1, 2, and 3 being central to the flow of advice, as reflected by their high Total and In-Degree centrality measures. The direct and non-hierarchical nature of this network, suggested by the absence of betweenness centrality, alongside the high Eigenvector centrality of the Clinical Professor, indicates an environment where professional advice is readily sought, contributing to a dynamic exchange of knowledge within the team.

### **Knowledge Of Network**

A critical analytic component in understanding Team J's resilience, particularly in the context of securing funding—a key driver of sustainability and growth for research teams. Convergence, defined as the depth of interdisciplinary integration essential for the co-creation in grant proposals, emerges as a vital element for successful funding applications (Bednarek *et al.*, 2023; Bolger, 2021; LaRosa, 2023b). This network serves as an indicator of the team's potential to amalgamate and apply comprehensive interdisciplinary knowledge, which is pivotal for crafting robust, competitive grant proposals. Through the lens of the Knowledge Of network, this analysis aims to elucidate the extent to which team members comprehend and can potentially synthesize their diverse disciplinary insights, thus highlighting their collective capability for interdisciplinary collaboration and innovation.

#### **Knowledge Of Network**

#### **Knowledge Of Box Plots**

In the analysis of Team J, the Knowledge Of network plays a pivotal role, employing weighted edges to quantify the self-reported comprehension among team members' respective fields of expertise, a key element in fostering interdisciplinary convergence. Figure 5.16 visualizes this network with varying edge boldness to signify the weight of the reported knowledge levels, distinguished by node colors that represent different faculty positions and a square node for the team lead. Complementing this, Figure 5.17 offers a box plot that aggregates the centrality measures within the network, reflecting a substantial variation of betweenness.

Betweenness and Out Degree are utilized within the “Knowledge Of” network to quantitatively assess the potential of interdisciplinary convergence and mutual

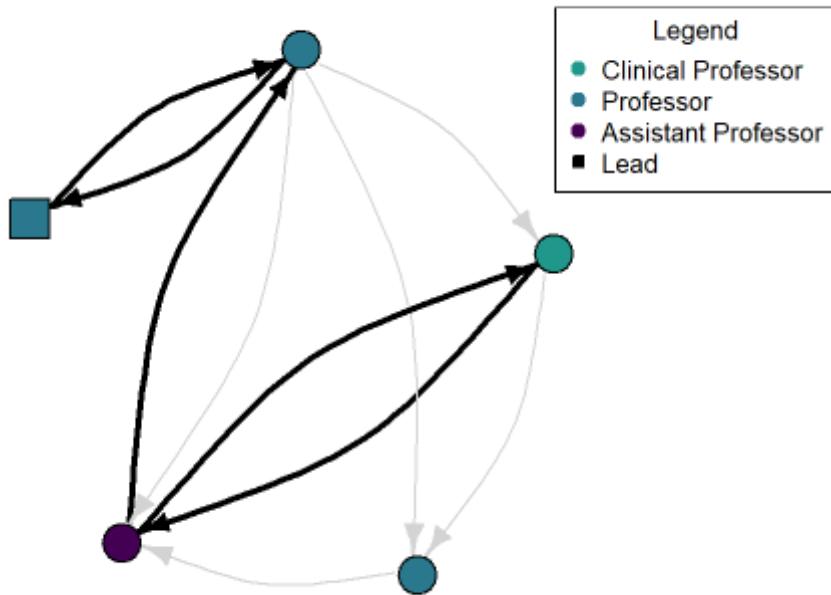
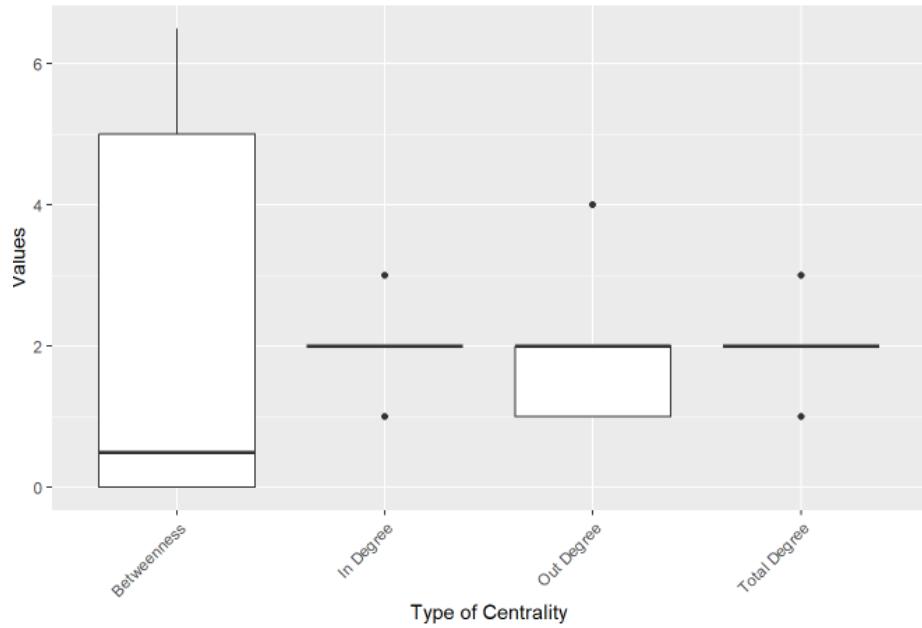


Figure 5.16: Knowledge Of Network plot shows edge weights become increasingly bolder as the weights become larger. The shape of the lead is square. The colors of the nodes differ by position.

comprehension among team members (see Table 5.10).

In the analysis of Betweenness centrality from the Knowledge Of Network, specific members of Team J demonstrate notable metrics that highlight their roles within the team's collaborative structure. Professor 1 shows a Betweenness centrality of 5.0, indicating that they play a significant role in connecting team members across different knowledge domains, likely serving as a bridge for information flow. Professor 3 has an even higher Betweenness centrality of 6.5, suggesting they are a central figure in the team's network, facilitating a considerable amount of knowledge integration among team members. In contrast, Clinical Professor 1 and Assistant Professor 1, with a Betweenness centrality of 0.0, are likely not acting as intermediaries in the network, which may suggest that their interactions are more direct with others, bypassing the



**Figure 5.17: Box Plot of the Knowledge Of Network Centrality Measures:** The box plot encapsulates the centrality measures within the Knowledge Of network, which is constructed from the survey responses indicating the level of disciplinary integration and mutual comprehension among team members. Team J researchers show a high degree for all team members, indicating that this team has a high level of knowledge about each other's expertise.

need for intermediaries.

Out-degree captures how well individuals can describe their colleagues' areas of expertise, reflecting their awareness and understanding of the team's collective skills. In the Knowledge Of network, Out Degree centrality is reflecting an individual's awareness and ability to recognize and describe the expertise of their colleagues, rather than their role in actively disseminating their own expertise. Therefore, when Professor 3 has an Out Degree of 4, it indicates a high level of awareness and understanding of four team members' disciplines, showcasing their broad recognition of team expertise rather than their direct provision of advice or knowledge to others. Similarly, lower Out Degree values for Clinical Professor 1 and Assistant Professor 1 suggest a more limited recognition of their colleagues' areas of expertise. This clarification necessi-

tates a revised interpretation of the roles and contributions within the team, focusing on the recognition of interdisciplinary knowledge rather than the dissemination of advice.

The prediction that individuals with high Out Degree centrality are likely in the Professor position or belong to teams with a predominance of within-discipline relations aligns well with observed patterns in the Knowledge Of network. Specifically, the high Out Degree centrality of Professor 3, indicative of a comprehensive understanding of team members' expertise, supports the thesis's anticipation of professors playing a central role in recognizing interdisciplinary knowledge within the team.

|                       | Total Degree | In Degree | Out Degree | Betweenness |
|-----------------------|--------------|-----------|------------|-------------|
| Clinical_Professor 1  | 1            | 1         | 1          | 0.0         |
| Professor 1           | 3            | 3         | 2          | 5.0         |
| Professor * 2         | 2            | 2         | 2          | 0.5         |
| Professor 3           | 2            | 2         | 4          | 6.5         |
| Assistant_Professor 1 | 2            | 2         | 1          | 0.0         |

**Table 5.10: Centrality Measures in the Knowledge Of Network for Team J:** This table delineates the centrality metrics—Total Degree, In Degree, Out Degree, and Betweenness—of team members within the Knowledge Of network. The measures are indicative of each member's position and quantify their self-assessed familiarity with the expertise of their colleagues. The Out Degree specifically reflects the extent to which individuals are aware of and can articulate the skills and knowledge areas of other team members, serving as a crucial indicator of the team's capacity for interdisciplinary collaboration and mutual understanding.

**Knowledge Of Discussion** The analysis within Team J's Knowledge Of network highlights significant roles played by members in enhancing interdisciplinary collaboration and resilience, with Betweenness centrality identifying Professors 1 and 3 as key connectors across diverse knowledge domains. Their roles are critical in integrating various disciplinary insights, essential for successful interdisciplinary research. Out Degree centrality showcases Professor 3's extensive understanding of team members'

expertise, contrasting with lower awareness levels in Clinical Professor 1 and Assistant Professor 1, suggesting areas for improvement in interdisciplinary synergy. These findings underline the importance of nurturing interdisciplinary connections to bolster team resilience and innovation potential. The analysis advocates for targeted efforts to deepen team members' interdisciplinary understanding, aiming to strengthen the team's cohesion and research capacity.

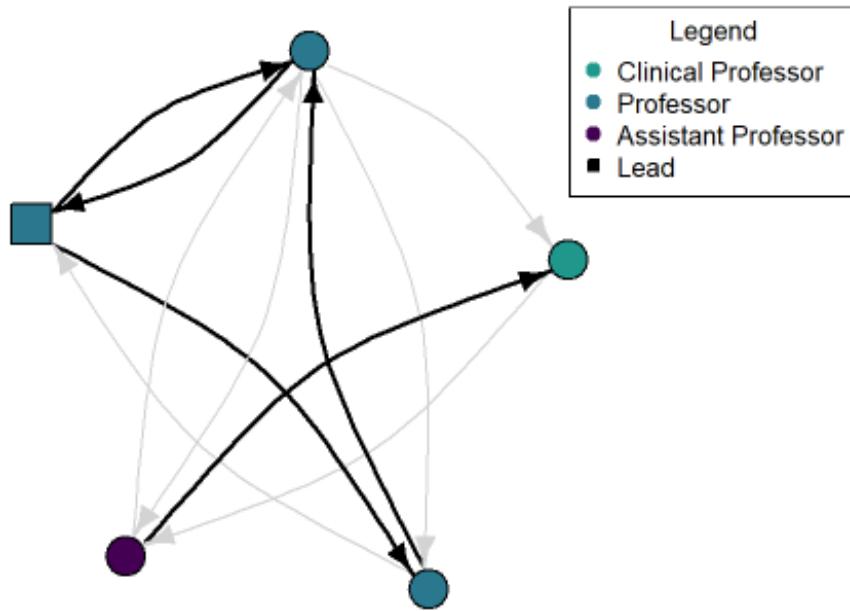
The degree of interdisciplinarity within teams plays a crucial role in interpreting centrality metrics. Team J is predominantly short-distance interdisciplinary relationships. This composition suggests a foundational level of disciplinary knowledge among members, facilitating basic comprehension and the convergence of disciplines included within the team.

### **Personal Networks**

Within the exploration of Team J's resilience, Personal networks illuminate the vital role of social connections in fostering a supportive and influential team environment. These networks, encompassing Personal Advice, Hang Out, and Personal Friend interactions, are indicative of a team member's capacity to mobilize resources and support, integral to the overarching goals of the GCs initiative.

The sublayer Personal networks, as visualized earlier in Figure 5.5, depict the informal social landscape of Team J, with each node representing an individual and the edges depicting the various personal interactions, whether seeking advice, forming friendships, or expressing the desire to socialize outside of professional settings. Team J's Personal network encompassing Personal Advice and Personal Friend and Hang Out is an empty network for this team. The aggregated two sub-layers, as an

appropriate methodology in section 5.5.1, form the multilayer network “Personal” and is visualized in Figure 5.19.



**Figure 5.18:** Personal Network plot shows the edge weights become increasingly bolder as the weights become larger. The shape of the lead is square. The colors of the nodes differ by position.

The Table 5.11 shows centrality measure for each team member of Team J. In Degree centrality measures the number of incoming ties to a node, demonstrating how often a member is sought out within the network. All team members, except Professor 3 who stands out with an In Degree of 3, have an In Degree of 2, indicating they are equally approached by others for personal interactions, advice, or support.

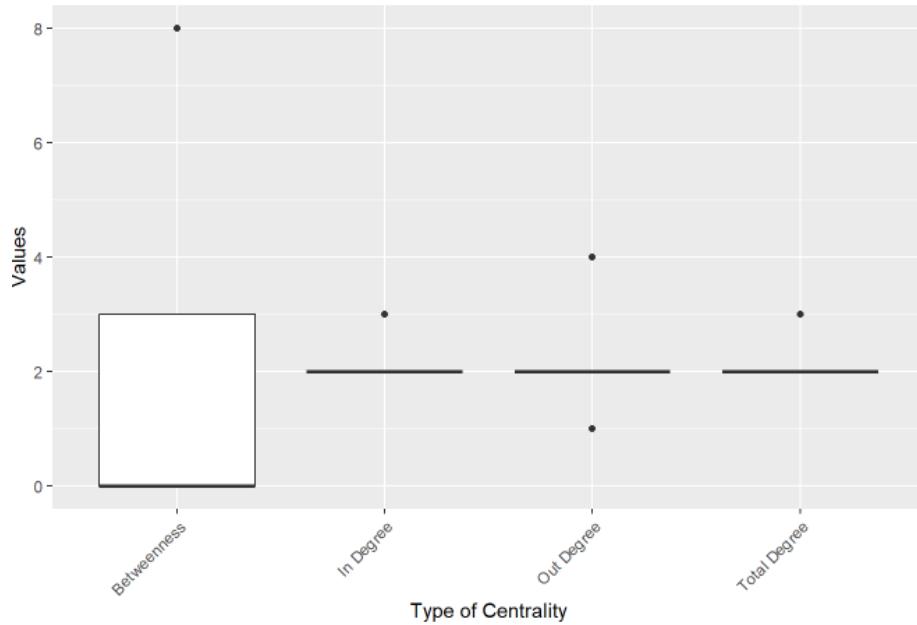
Out Degree centrality counts the outgoing ties, showing the extent to which individuals reach out to others. Professor 3’s Out Degree of 4 highlights their proactive role in seeking connections, advice, or support, further underscoring their active participation in the team’s social fabric.

|                       | Total Degree | In Degree | Out Degree | Betweenness |
|-----------------------|--------------|-----------|------------|-------------|
| Clinical_Professor 1  | 2            | 2         | 2          | 0           |
| Professor 1           | 2            | 2         | 2          | 3           |
| Professor * 2         | 2            | 2         | 1          | 0           |
| Professor 3           | 3            | 3         | 4          | 8           |
| Assistant_Professor 1 | 2            | 2         | 2          | 0           |

**Table 5.11: Personal Network Centrality Measures for Team J:** This table presents the centrality metrics—Total Degree, In Degree, Out Degree, and Betweenness—for each member within Team J’s Personal network. These measures reflect the extent and nature of personal interactions among team members, from advice-seeking to social engagements. Total Degree indicates the overall level of a member’s connections, In Degree shows how often a member is sought out, Out Degree reflects a member’s outreach, and Betweenness centrality reveals their role as intermediaries in social interactions. Professor 3’s high Betweenness score, in particular, highlights their central role in facilitating personal connections within the team.

Betweenness centrality, with Professor 3 displaying the highest value of 8, identifies individuals who act as bridges in the social structure, facilitating interactions between members who may not directly connect. Professor 3’s prominent Betweenness score underlines their crucial role in the diffusion of social capital and enhancing social cohesion, acting as a conduit for information and resources across the team. In contrast, the zero Betweenness scores for Clinical Professor 1, Professor \* 2, and Assistant Professor 1 suggest these members do not typically mediate interactions between others, indicating a more direct flow of communication within the team.

The degree distribution within Team J’s Personal network, as illustrated in Figure 5.19, suggests a relatively uniform engagement among team members. Total Degree and In Degree both exhibit a narrow range, consistently spanning between 2 and 3, which implies a balanced level of connectivity and that members are generally equally sought out for personal interactions. The somewhat wider range in Out Degree, from 1 to 4, reveals variability in how actively members seek out others for personal engagement. Notably, one individual stands out with a higher Out



**Figure 5.19: Box Plot of the Personal Network Centrality Measures:** The box plot encapsulates the centrality measures within the Personal network, which is constructed from the aggregated

Degree, indicating a more proactive approach to seeking personal connections within the team. This distribution pattern indicates a cohesive team environment with no member being significantly more central or isolated in terms of personal interactions, which is conducive to effective collaboration and team resilience.

**Personal Network Discussion** The analysis of Team J's Personal networks offers critical insights into the team's social dynamics, which are fundamental to its resilience. The centrality measures reveal that Professor 3 is a key player in Team J's social fabric, as evidenced by their high Out Degree and Betweenness centrality. They are not only actively seeking personal interactions but also serving as a linchpin in the team's interpersonal connectivity, indicative of their central role in both fostering relationships and facilitating resource mobilization within the team.

This proactive engagement in personal networks is crucial within the context of

the GCs initiative, as it aligns with the strategic aim to cultivate a collaborative and supportive research environment. The distribution of centrality measures suggests that while Professor 3 stands out for their social initiative and bridging capacity, the team overall enjoys a relatively even distribution of engagement levels, with most members being equally integrated into the network of personal interactions.

Such a pattern of connectivity signifies a harmonious balance of influence and support among team members, contributing to a cohesive team climate. This balance is crucial for maintaining team stability and adaptability, as it indicates an environment where social support is accessible, and collaborative relationships are maintained without over-reliance on any single individual. As a result, Team J is well-positioned to capitalize on its social networks for collaborative success, resilience in the face of challenges, and continued growth in line with the objectives of the GCs initiative at Boise State.

## 5.6 Conclusion

The analysis section meticulously articulated a methodological framework for assessing the GCs initiative's impact at Boise State. The initiative aims to enhance scientific productivity, mentoring, transdisciplinarity, convergence, and interpersonal relationships within each research team. By delineating the specific network treatments and goals for Leadership, Award, and IRA teams, this framework underscores the complexity of evaluating productivity against diverse team objectives. The strategic focus on fostering an environment conducive to interdisciplinary collaboration, mentorship, and developing resilient research communities forms the crux of the anticipated outcomes. In the analysis section, the emphasis will be on applying SNA to scrutinize these identified variables in depth. This approach will enable a granular examination

of how GCs' investments influence research collaboration at the university. The forthcoming analysis is poised to unravel the initiative's efficacy in promoting an equitable, inclusive, and innovative research landscape by measuring the initial state of the outlined variables. By exploring the dynamics of scientific productivity, assessing the richness of experiential diversity, understanding the depth of mentoring interactions, gauging the breadth of interdisciplinary collaboration, and analyzing the strength and quality of interpersonal relationships, this section aims to provide actionable insights into the transformative potential of the GCs initiative at Boise State.

## CHAPTER 6: DISCUSSION

### 6.1 Collaboration Review

### 6.2 Most Important Finding

### 6.3 Boise State's Blue Print Goals

### 6.4 Study Limitations

### 6.5 Practical Recommendations

### 6.6 Future Research

### 6.7 New and Expanded Opportunities

The 2020 historical grant proposal's whole network metrics suggest that scholars shared a more equal distribution of co-proposers (Table 4.2: mean degree) and an increase in structural cohesion (Table 4.3: density, Table 4.2 connectedness). This is indicative of collaborative grant proposing faculty engaging in larger, more interconnected groups. The COVID-19 pandemic may have driven researchers towards more significant, cross-disciplinary collaborations (Table 4.3: density, Table 4.2: clustering coefficient, average path length). Future research should verify that the 2020 network

has an increased number of co-proposers from various disciplines.

However, future research should also determine if less established researchers are generally missing from the 2020 network compared to the previous years. This network had the lowest number of faculty engaging in grant proposals (network size), the lowest number of proposals, collaborative (Table 4.1: collaborative proposal count) or otherwise (Table 4.1: proposal count), and the reduction of gatekeepers or mentors (Table 4.2 mean betweenness) in the network compared to all other years. This suggests that those lacking robust social connections, mentorship, and interdisciplinary collaboration experience found it more challenging to secure collaborative grant-proposing opportunities. The higher mean degree could indicate a consolidation of collaborative activity among a smaller number of researchers. The consolidation of collaboration, evidenced by higher clustering, may indeed reflect a scenario where well-established researchers leveraged their existing social capital to maintain productivity in the face of the pandemic's isolation.

Therefore, the whole network metrics interpretation in this thesis posits that the behavioral response to the COVID-19 pandemic exposed a concentration of resources among researchers with stronger networks, echoing Sonnenwald ? observation of how established researchers can form influential groups.

The GCs initiative emphasizes mentorship and the democratization of opportunity across the university community to create a thriving community (Boise State University, 2024) during challenging periods. Norton *et al.* (2017, p.2-3) highlight the importance of documenting and understanding collaborative dynamics to alter ineffective practice and aid in fostering collaboration for new and upcoming researchers.

Future research by the SNAP could be directed towards a more nuanced under-

standing of collaborative equity within the grant proposal networks. One method to quantitatively assess this aspect involves the application of the Gini coefficient to the degree distribution of these CUPID networks. The Gini coefficient, a widely recognized measure of inequality within a distribution (Kelly *et al.*, 2014), can elucidate the concentration of collaborative efforts across faculty members. Typically employed in economics to assess income disparities, this coefficient has also found relevance in bibliometric studies and social network analysis as a means to evaluate the balance of collaborative interactions (Chien *et al.*, 2018; Liu *et al.*, 2020; Leydesdorff *et al.*, 2019).

For Boise State's collaborative network, the Gini coefficient could indicate whether co-proposalship is evenly spread across the faculty (a Gini coefficient near 0) or whether it is dominated by a select few (a Gini coefficient approaching 1) (Kelly *et al.*, 2014). This would be particularly insightful when considering the inclusiveness of less established researchers in the collaborative processes. SNAP's approach, which would not exclude the network's absent nodes, assumes that all faculty had the potential to engage in grant collaborations, providing a comprehensive overview of the network's collaborative dynamics. The resulting insights could critically inform the effectiveness of the GCs initiative in fostering inclusive and diverse research collaborations across the campus.<sup>1</sup>

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<sup>1</sup>The Lorenz curves, derived from the Gini coefficient calculations to visualize the distribution of degree centrality, are provided in Appendix B for detailed reference and further analytical exploration.

## 6.8 GC Teaming Limitations

### 6.8.1 Politics and Its Influence on Research Freedom

The broader political environment can influence the pursuit of innovative solutions within academic research, such as those endeavored by the GCs initiative. Political factors often shape research agendas, especially concerning wicked problems that intersect with public policy and societal issues. In navigating these political landscapes, research initiatives may face challenges that require cautious strategy, potentially influencing the scope and direction of their inquiry.

For instance, during the planning phase of the GCs, the selection of thematic areas for research was influenced by the prevailing political climate. Originally proposed topics, some of which delved into areas of equity and justice, were reassessed considering the time's broader political and social context (LaRosa, 2023b, personal communication, September 25). Such decisions highlight the complex interplay between academic freedom and political considerations, underscoring the delicate balance research initiatives must maintain.

Furthermore, research projects that delve into areas of social and political sensitivity can encounter unique challenges. For example, certain research plans within the GCs initiative faced delays and adjustments due to their intersection with contentious issues (LaRosa, 2023b, personal communication, September 25). These incidents underscore the intricate balance required between academic exploration and political realities. Such experiences are not unique to any particular institution or state but reflect a common challenge faced by researchers globally: navigating the delicate interface between academic inquiry and the political landscape.

### 6.8.2 Future Research: Low Hanging Fruit

#### Publications (CATNIP)

A common network type used to evaluate research collaboration is journal publications. The next phase of SNAP will include an analysis of Boise State's publication network. This can be useful in understanding the collaboration at Boise State as a whole and also in determining each LOVE team's scientific productivity and interdisciplinary publications prior to the network treatments.

#### Adding Node Attributes to CUPID

An node attribute that could be included in future studies includes attendance of team science training. The CRCA hosts a team science training each semester for any facility member to attend (LaRosa, 2023b, personal communication, September 25). While this study did not include attendance to these programs, the team science training roster is available (See Michelle Grek for CRCA Events Attendance Log). This could be included as a node attribute for GCs team members to help understand differences in team success.

Future research could limit which colleges are included so as to investigate the interdisciplinary interactions among targeted colleges. Sciabolazza *et al.* (2017) limited the colleges they longitudinally investigated when studying publications and awarded grant networks at the University of Florida.

Speaking of awarded grant networks, future research could also investigate the Boise State's awarded grant network. These networks were created but not analyzed in this thesis.

### **Expanding LOVE Team Roster**

However, the forthcoming mid-network treatment survey aims to broaden the team's composition. This survey will include individuals who may not be directly involved in research at BSU, thereby introducing new perspectives and expertise to the team. Addressing the methodological challenges posed by this expansion is crucial. It requires careful consideration to ensure that the integration of new team members aligns with the overarching goals of the U-SIP project and enhances its multidisciplinary approach.

### **Network ethnography: LOVE team**

Network ethnography poses an additional benefit to measuring scientific productivity. Leite & Pinho (2017, p. 95) note that while some researchers worry about the perceived lack of objectivity in qualitative indicators, any indicator can be quantified and analyzed statistically to ensure objectivity.

### **LOVE Leadership**

Further research may consider investigating the personality characteristics of interdisciplinary team leaders to customize leadership training and extend the specific resources to fill the leader's gaps.

## **CHAPTER 7:**

## **CONCLUSION**

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## APPENDIX A:

### CUPID NETWORK VISUALIZATIONS

Appendix A includes network visualizations representing the collaborative grant proposals for each individual year within the 2016 to 2020 period. These yearly visualizations provide an in-depth view of the evolving collaborative landscape and are available for review to complement the aggregated five-year network analysis presented in the main body of the text.

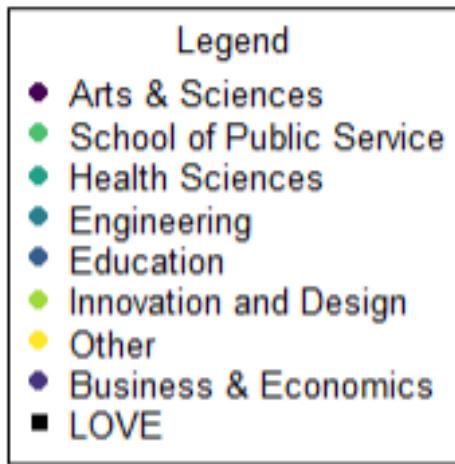


Figure A.1: Legend for the network visualizations of Boise State University's collaborative grant proposals. The colors denote the college affiliation of the researchers: Arts & Sciences (dark purple), School of Public Service (green), Health Sciences (black), Engineering (turquoise), Education (dark blue), Innovation and Design (light blue), and Other (yellow). Nodes representing researchers from the College of Business & Economics are shown in orange. The square-shaped nodes labeled "LOVE" indicate researchers who are members of at least one of the Grand Challenges teams, a topic elaborated upon in Chapter 5, signifying their involvement in strategic research initiatives.

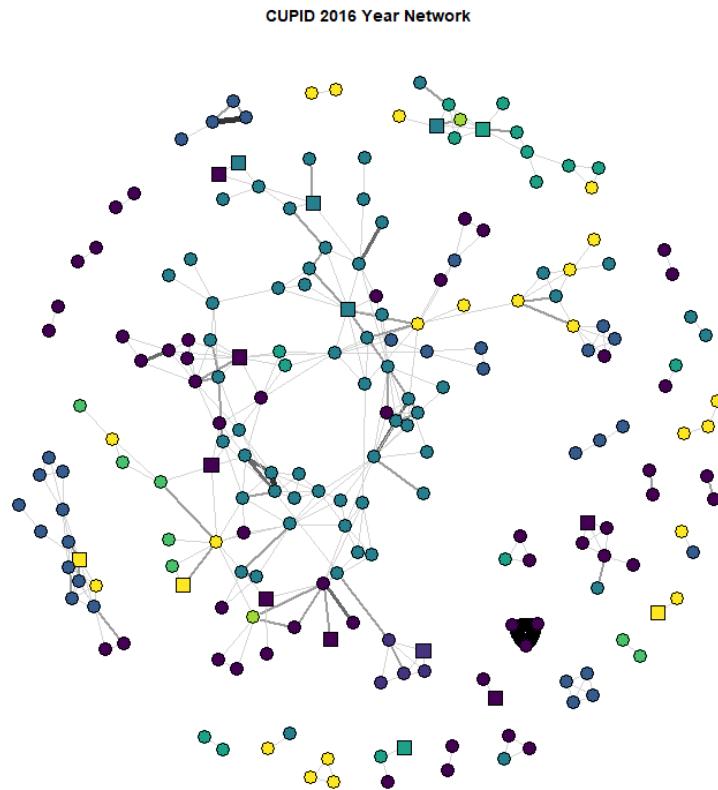


Figure A.2: Network visualization of Boise State's collaborative grant proposals for the year 2016. Nodes represent individual researchers, color-coded by college affiliation, and sized according to the number of collaborations. Edges indicate shared grant proposals, with a thickness corresponding to the number of shared projects. Squares denote members of GCs teams. The graph illustrates the connectivity within and across different colleges, highlighting the collaborative structure and isolated clusters within the university's research community for the specified year.

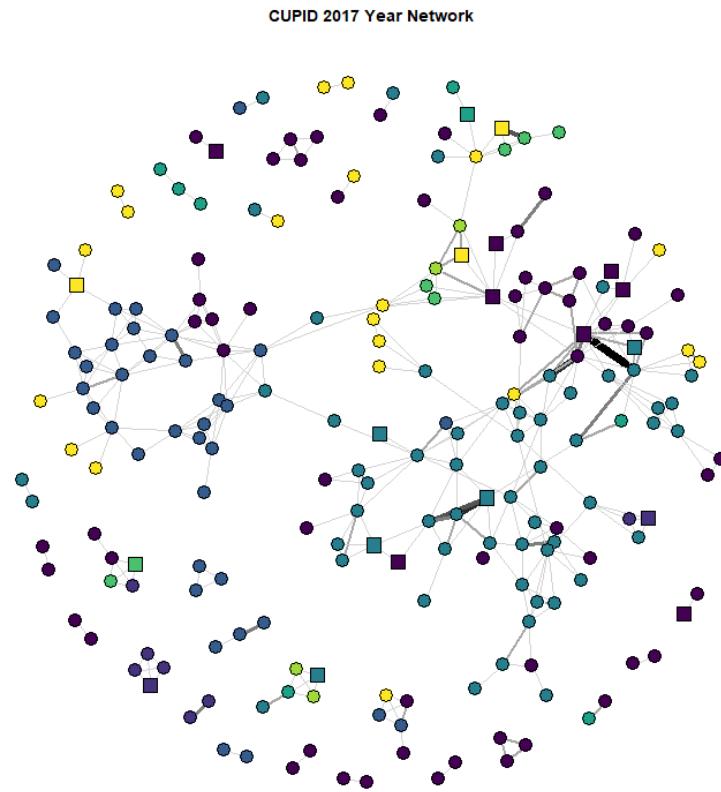


Figure A.3: Graphical depiction of the collaborative patterns in grant proposal submissions at Boise State University for the calendar year 2017. This network map details the interlinkages among researchers, with node color representing their college association and node size reflecting collaboration frequency. Connections between nodes illustrate co-authored grant proposals, with the edge width proportional to the collaboration count. Square nodes highlight individuals participating in GCs teams. The structure of the network underscores both densely interconnected clusters and more isolated research partnerships within the academic landscape for this year.

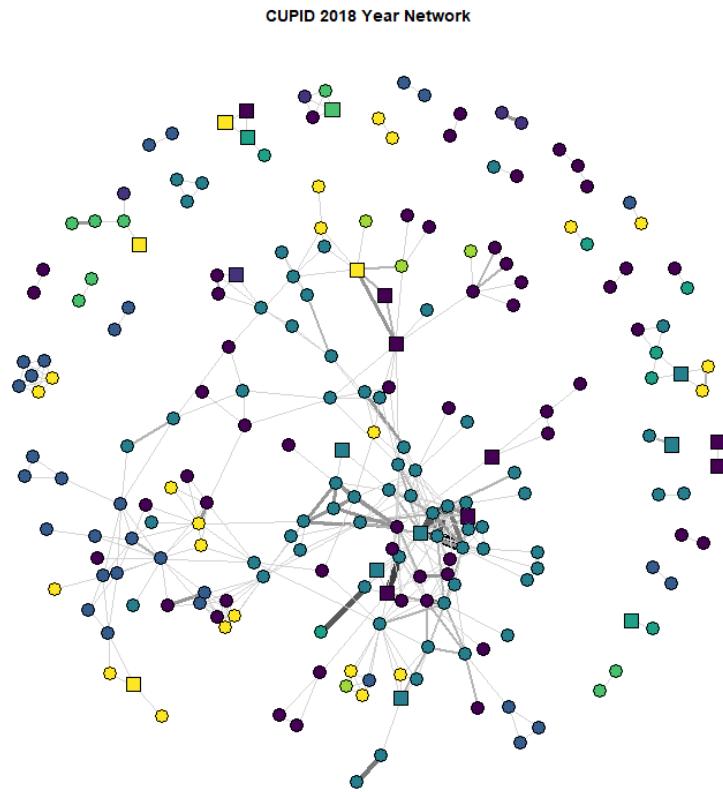


Figure A.4: Schematic representation of Boise State University's interdisciplinary grant proposal collaborations for the year 2018. Each node symbolizes an individual faculty member, differentiated by color to denote college affiliation and scaled to represent the extent of their collaborative engagements. Linkages between nodes are indicative of joint grant submissions, with the thickness of the lines correlating to the frequency of collaborative efforts. Square nodes identify faculty members involved in GCs teams. The diagram highlights the network's intricate web of connections, delineating both concentrated clusters of collaboration and disparate, loosely connected groupings within the university's scholarly community for the year in question.

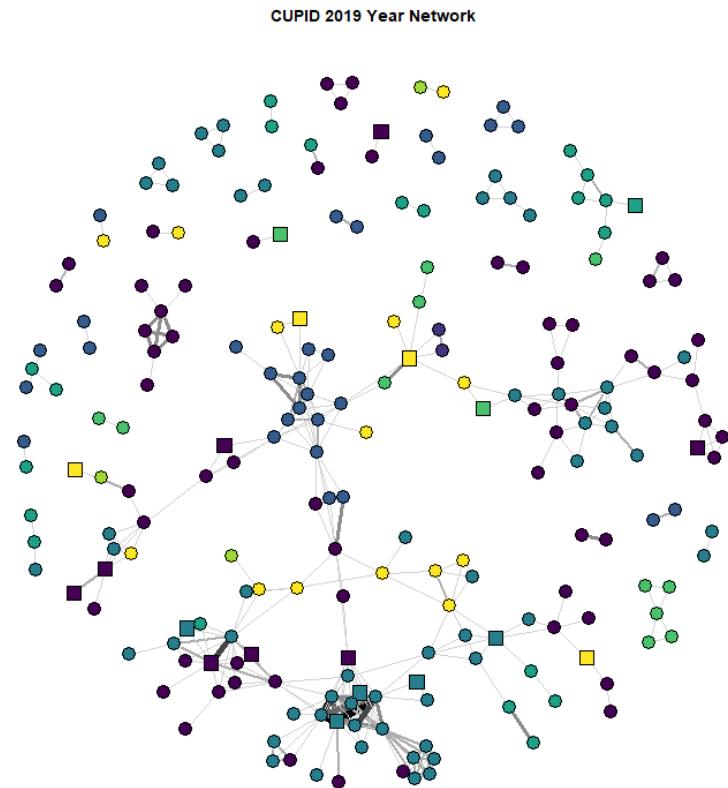


Figure A.5: Visualization of Boise State University's grant proposal co-authorship network for the year 2019. The nodes are keyed to faculty members, with varying colors representing different college affiliations, and the size of the nodes reflects the volume of collaborative activities. The relational ties, depicted as edges, correspond to co-authored grant proposals, with their widths proportional to the number of collaborations. Faculty members who are part of GCs teams are distinguished by square-shaped nodes. This network map serves to illustrate the patterns of academic collaboration, highlighting areas of concentrated interdisciplinary interaction as well as more isolated clusters within the university's research framework for the specified year.

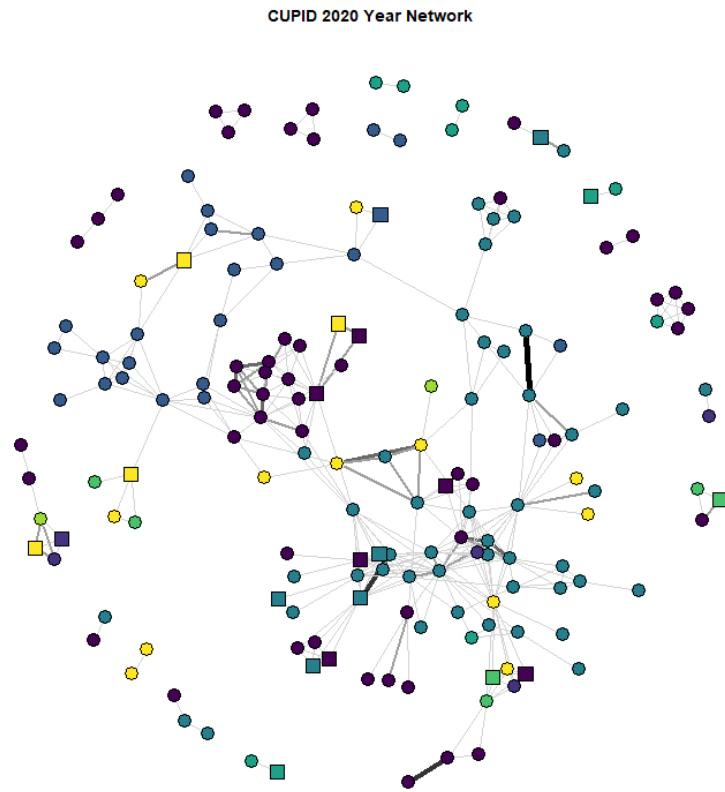


Figure A.6: Network diagram of Boise State University's collaborative grant proposal activities for the year 2020. The nodes symbolize researchers, with color coding aligned to their respective college affiliations, and their size indicative of the number of collaborative connections. Edges represent co-authored grant proposals, with varying thicknesses to indicate the number of joint proposals. Square nodes denote researchers involved with GCs teams. This visualization portrays the network's structure and highlights the collaborative trends, including densely connected nodes that suggest robust interdisciplinary engagements, as well as peripheral nodes indicating specialized or emerging collaborations.

## APPENDIX B: CUPID LORENZ CURVE

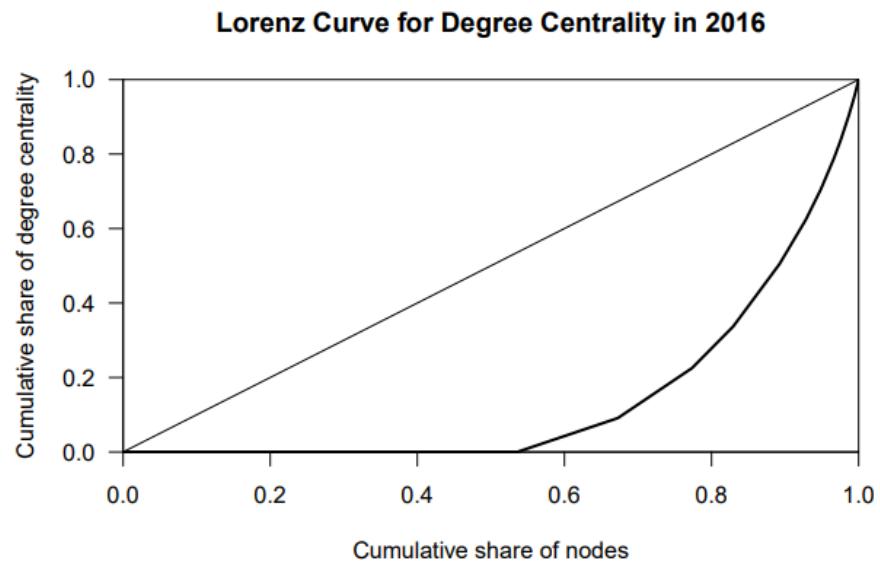


Figure B.1

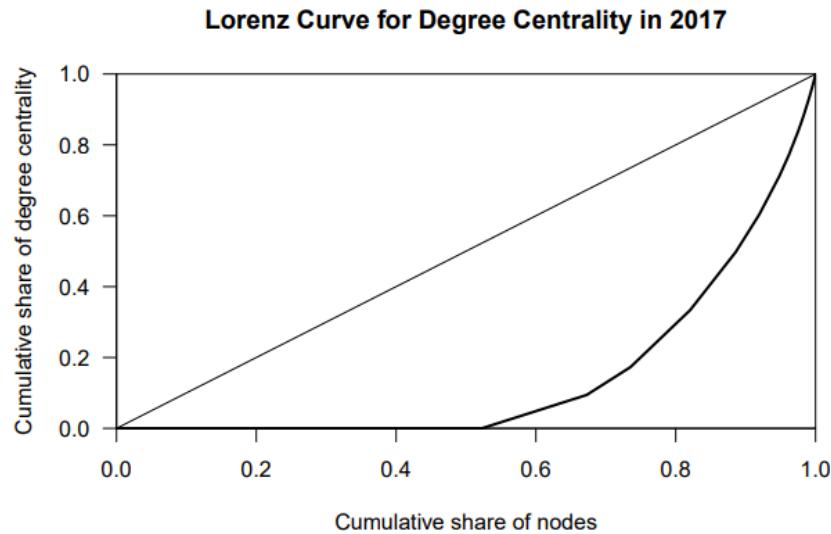


Figure B.2

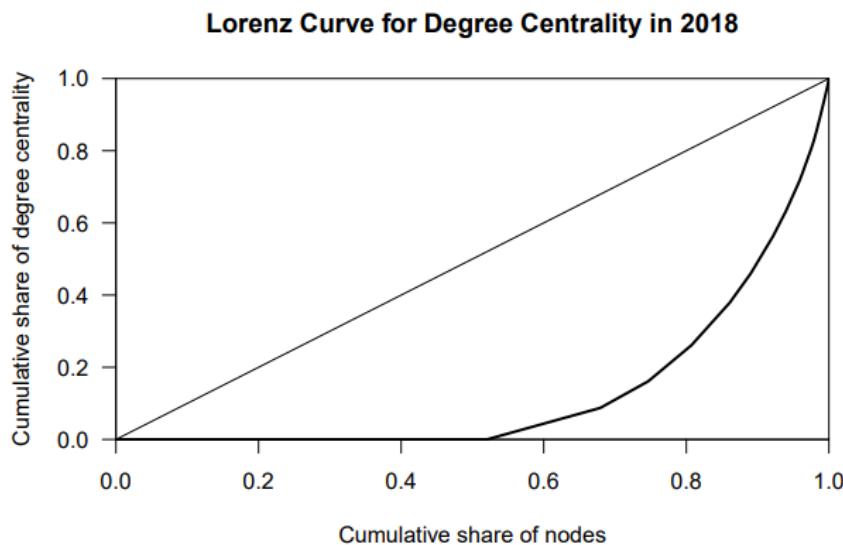


Figure B.3

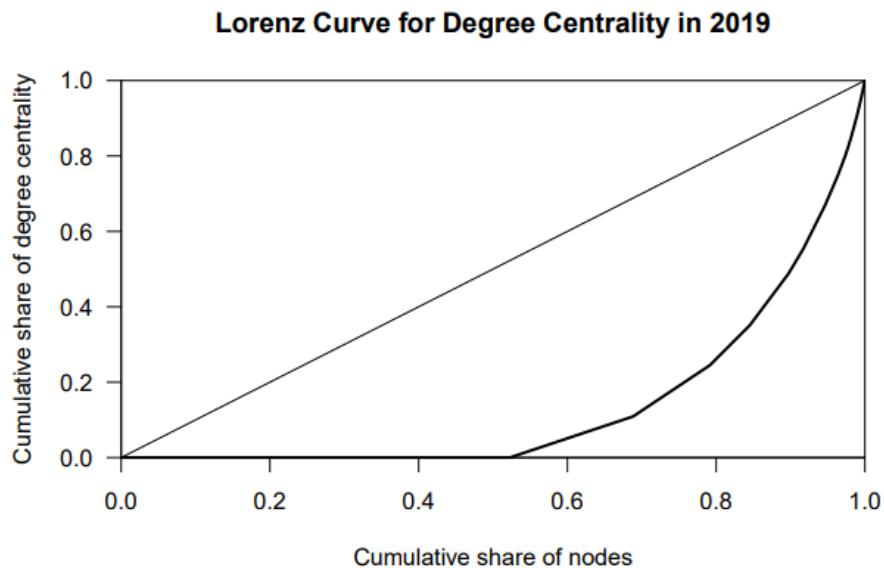


Figure B.4

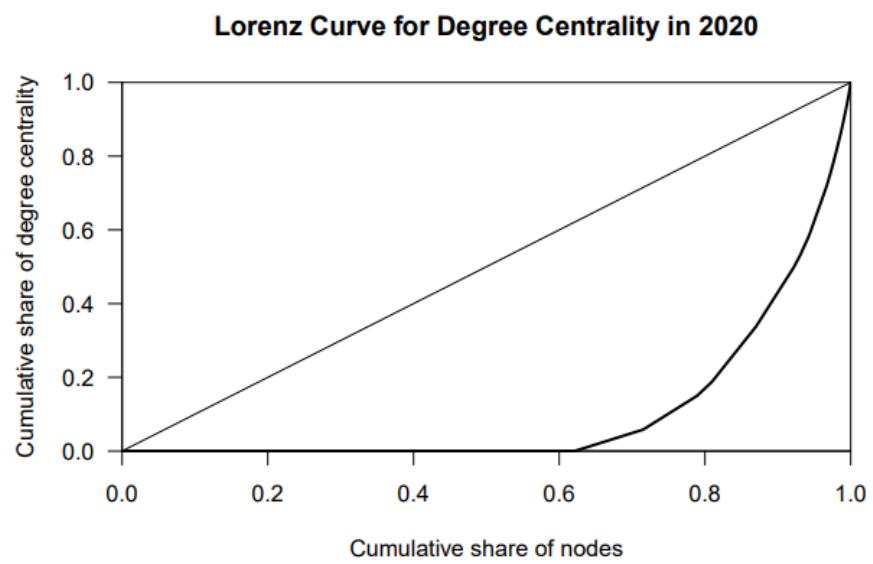


Figure B.5

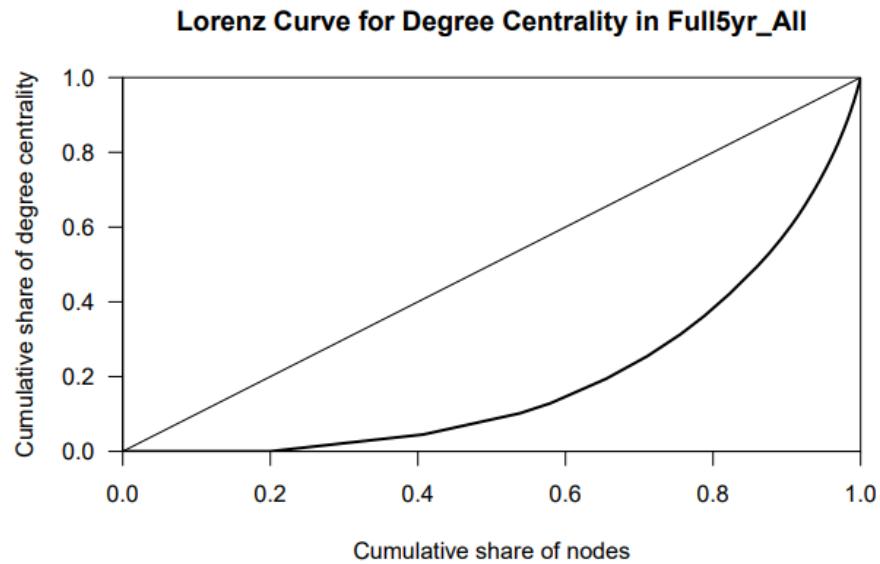


Figure B.6

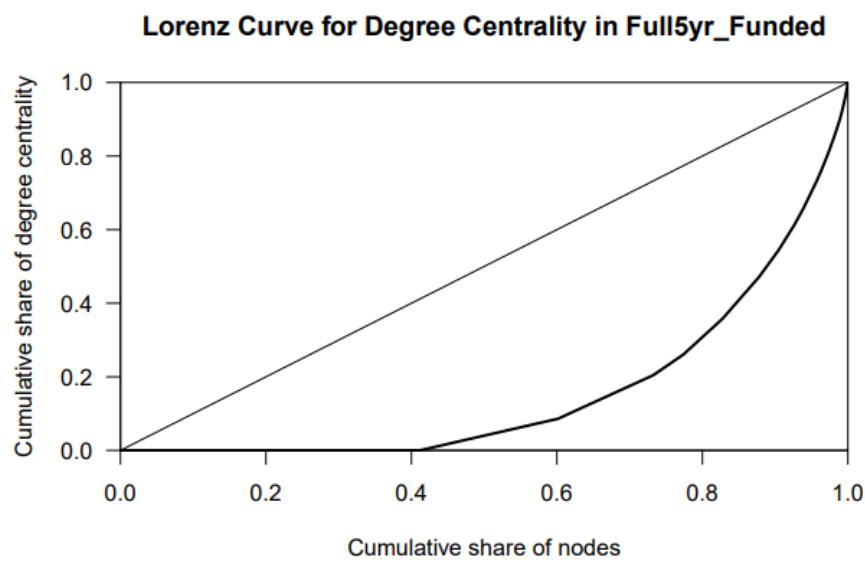
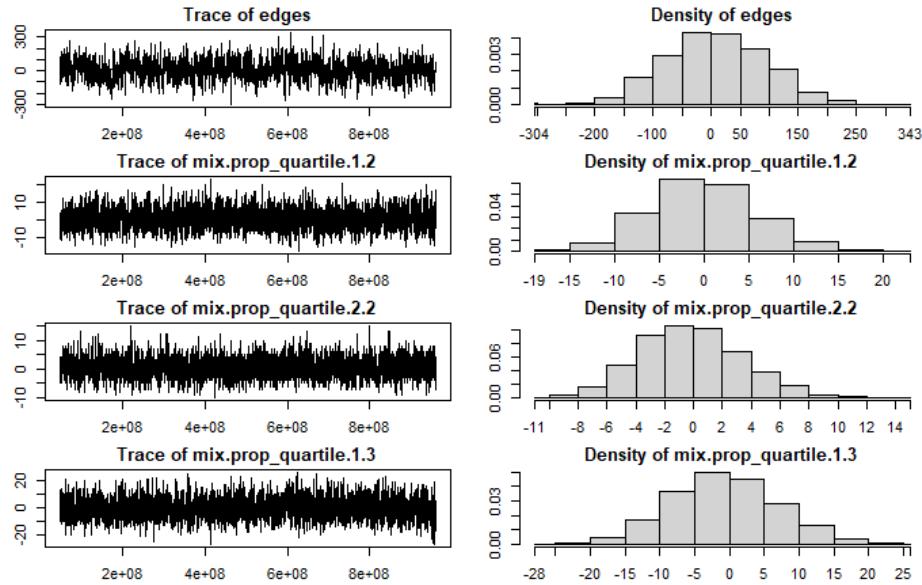


Figure B.7

## APPENDIX C:

### CUPID MCMC DIAGNOSTICS

Graphic diagnostics show the model in its final iteration. Should the model achieve convergence, the depicted graphics are expected to center each statistic at a mean value of 0 (Harris, 2014, p. 74). The inspection of the plots led to the conclusion that the final selected model did converge.



**Figure C.1**

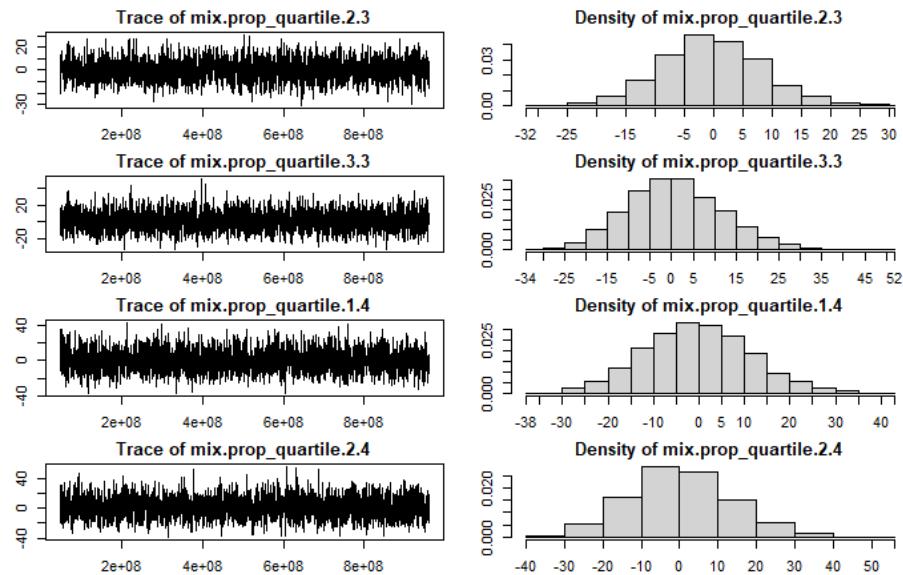


Figure C.2

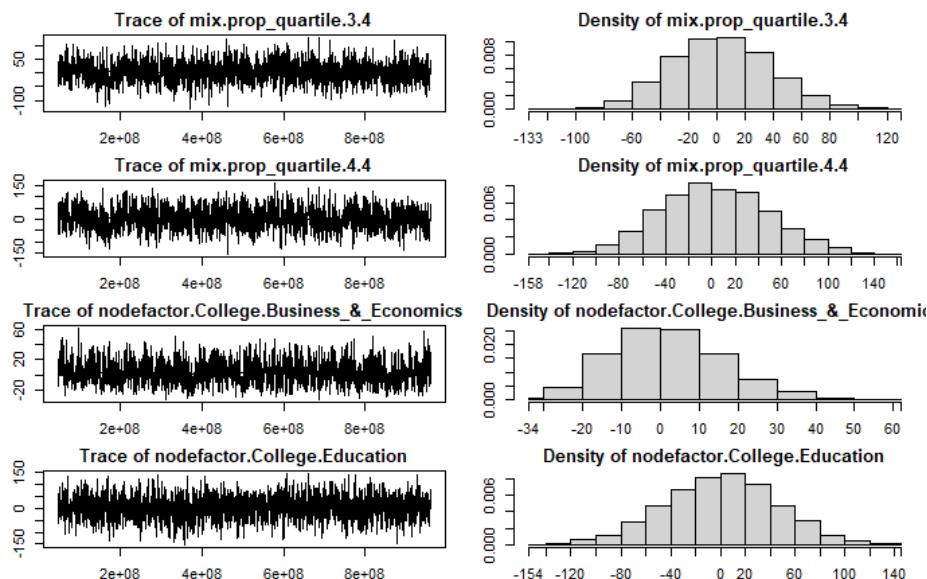


Figure C.3

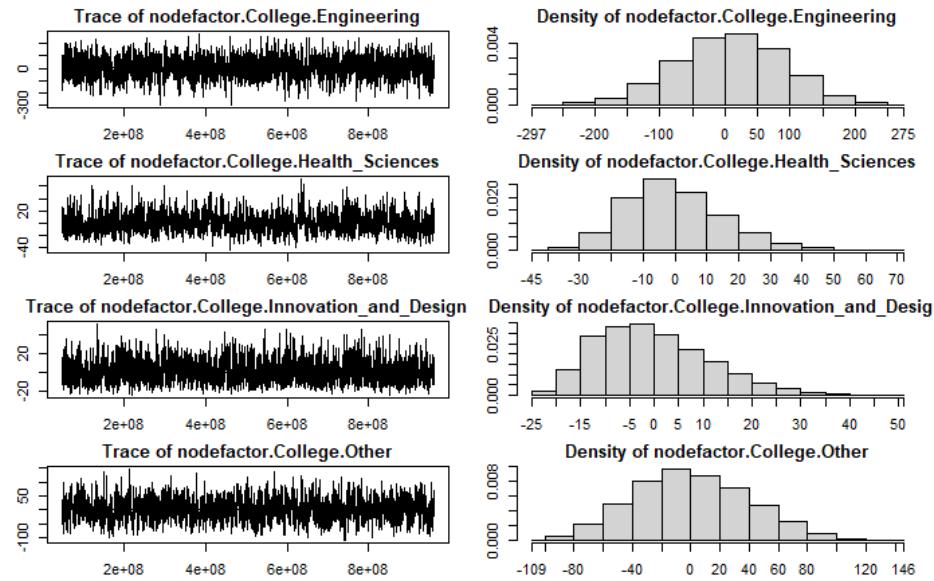


Figure C.4

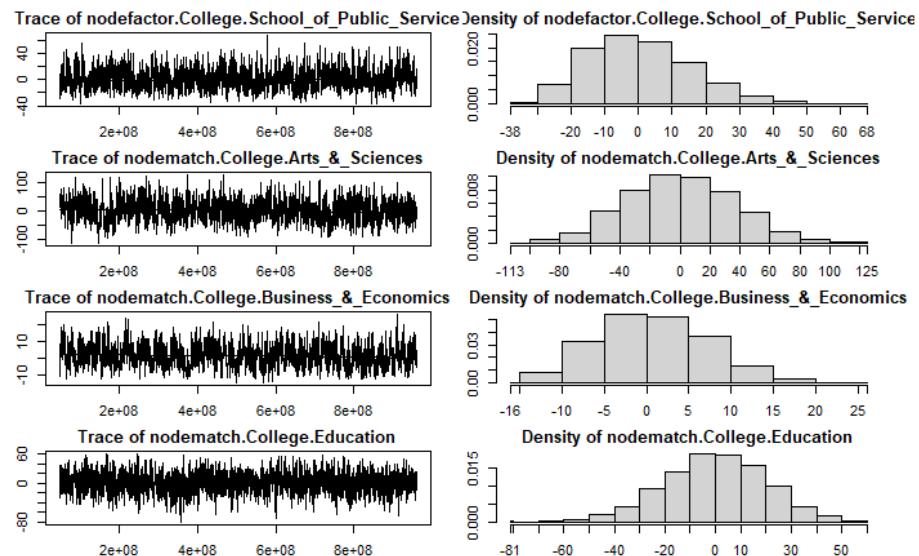


Figure C.5

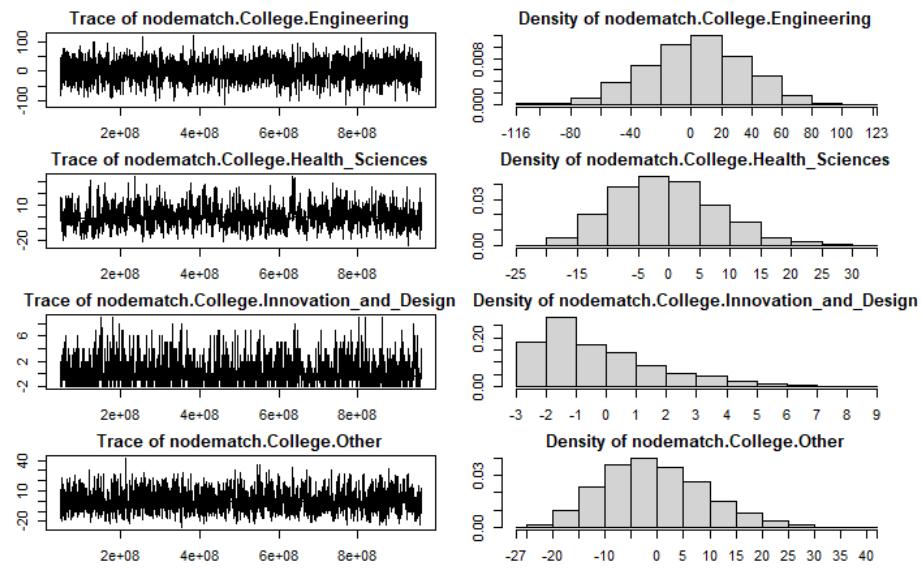


Figure C.6

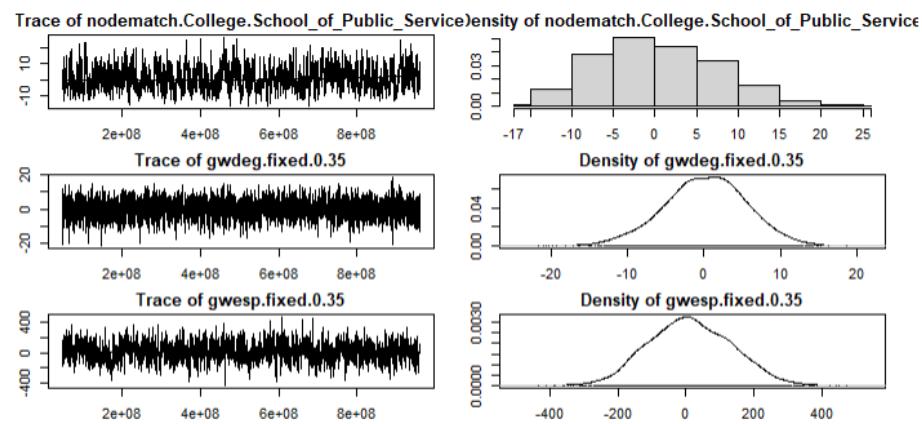


Figure C.7

## APPENDIX D: CUPID GOODNESS OF FIT PLOTS

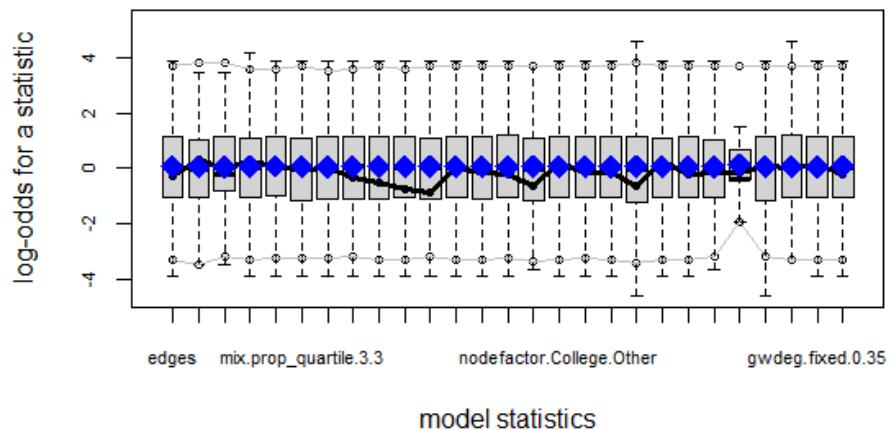


Figure D.1

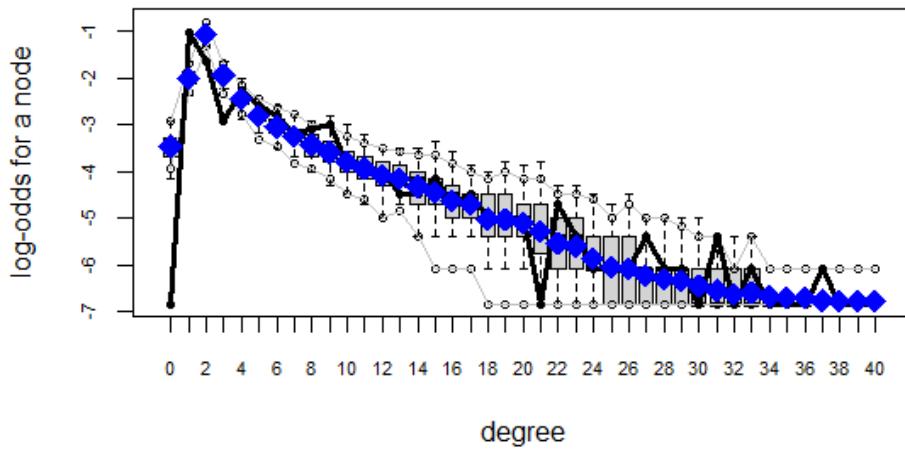


Figure D.2

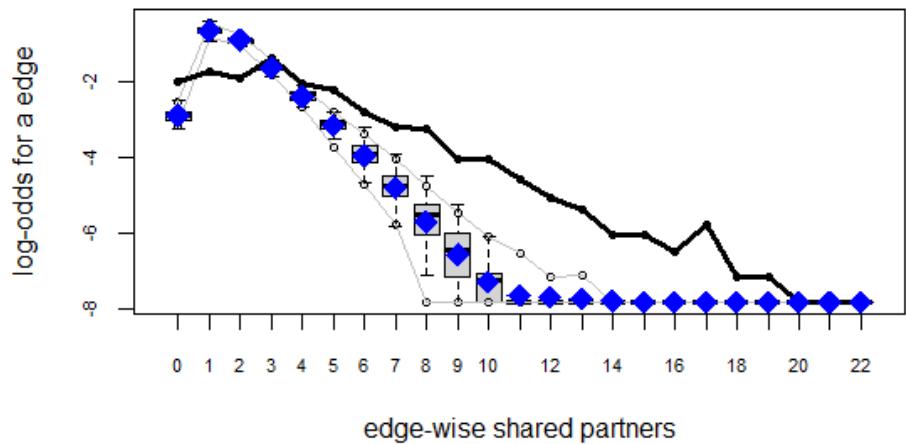


Figure D.3

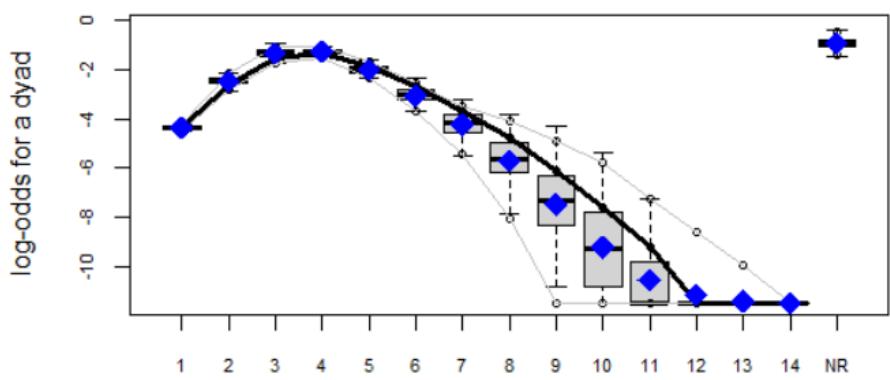


Figure D.4

## APPENDIX E:

### CUPID ESP & DSP DISTRIBUTION

Edgewise Shared Partners (ESP) is a concept that identifies pairs of connected nodes within a network that also share a mutual connection to at least one other node. This phenomenon is critical in understanding the network's clustering tendencies, as each triangular configuration contributes to three ESP instances, effectively tripling the number of triangles in the network's total ESP count (Harris, 2014, p. 42). The presence of multiple shared partners between a single pair of nodes often indicates the existence of tight-knit clusters within the network, with the ESP distribution offering insights into the network's overall propensity for such clustering (Harris, 2014, p. 42).

The related concept of Dyadwise Shared Partners (DSP) extends this analysis to pairs of nodes that may not be directly connected but share a common link to a third node. This measure is pivotal in assessing the network's transitivity potential, as an unlinked pair with shared partners is merely one connection away from completing a triangle, thereby fostering multiple triangular formations. The DSP distribution within a network sheds light on the prevalence of such indirectly connected pairs, typically exceeding what random chance would predict. This excess indicates a significant level of transitivity within the network, pointing to a structural predisposition for the formation of transitive ties (Harris, 2014, p. 42).

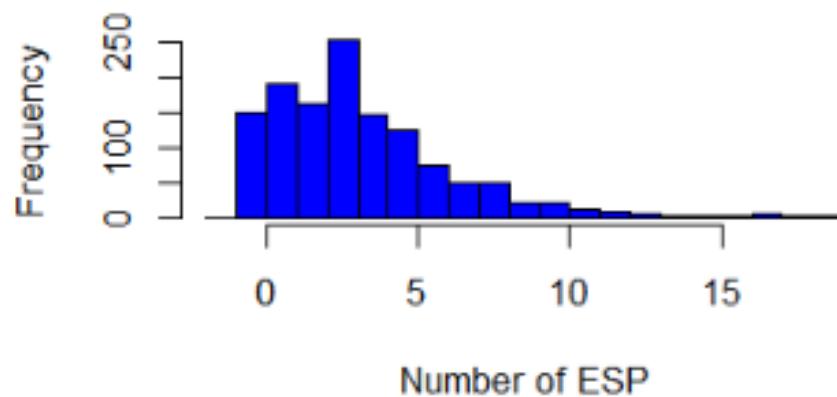


Figure E.1: Histograms of Edgewise-Shared Partners Distribution for Five Year Grant Proposal Network

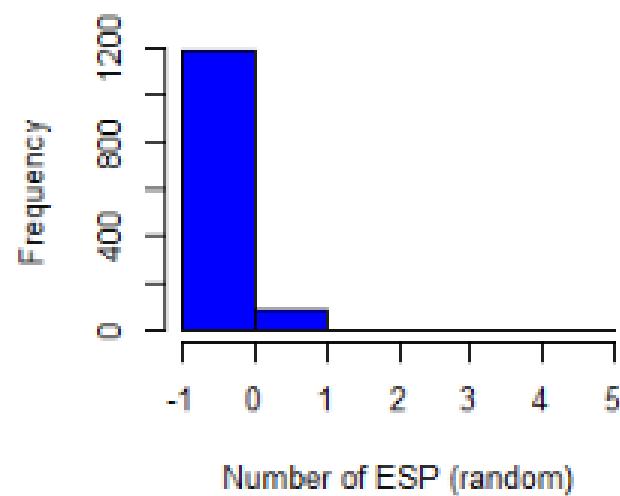


Figure E.2: Histograms of Edgewise-Shared Partners Distribution for a random network

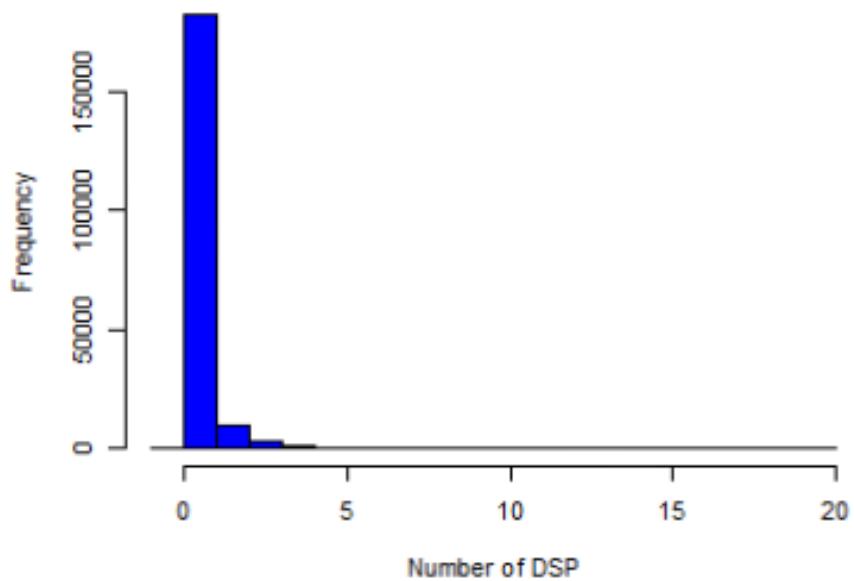


Figure E.3: Histograms of Dyadwise-Shared Partners Distribution for Five Year Grant Proposal Network

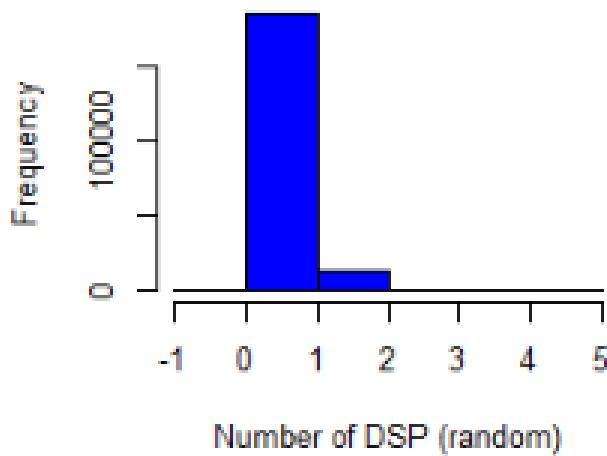


Figure E.4: Histograms of Dyadwise-Shared Partners Distribution for a random network

## APPENDIX F:

### CUPID ERGM SUMMARY

```

Call:
ergm(formula = network_Full5yr_All ~ edges)

Maximum Likelihood Results:

      Estimate Std. Error MCMC % z value Pr(>|z|)
edges -4.33449   0.02809     0 -154.3   <1e-04

edges ***
---
Signif. codes:
0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Null Deviance: 137569 on 99235 degrees of freedom
Residual Deviance: 13716 on 99234 degrees of freedom

AIC: 13718  BIC: 13727 (Smaller is better. MC Std. Err. = 0)

```

**Figure F.1: Null ERGM Summary**

```

Call:
ergm(formula = network_Full5yr_All ~ edges + nodematch("college",
  diff = TRUE))

Maximum Likelihood Results:

Estimate Std. Error MCMC % z value Pr(>|z|)
edges -5.12573 0.04606 0 -111.279 < 1e-04 ***
nodematch.College.Arts_&_Sciences 1.39785 0.08465 0 16.512 < 1e-04 ***
nodematch.College.Business_&_Economics 3.17982 0.27984 0 11.363 < 1e-04 ***
nodematch.College.Education 2.40733 0.09840 0 24.466 < 1e-04 ***
nodematch.College.Engineering 2.58618 0.07143 0 36.206 < 1e-04 ***
nodematch.College.Health_Sciences 2.08270 0.18671 0 11.155 < 1e-04 ***
nodematch.College.Innovation_and_Design 2.87444 0.74482 0 3.859 0.000114 ***
nodematch.College.Other 1.16810 0.16809 0 6.949 < 1e-04 ***
nodematch.College.School_of_Public_Service 2.73927 0.26527 0 10.326 < 1e-04 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Null Deviance: 137569 on 99235 degrees of freedom
Residual Deviance: 12244 on 99226 degrees of freedom

AIC: 12262 BIC: 12347 (smaller is better. MC Std. Err. = 0)

```

Figure F.2: Edges and Nodematch ERGM Summary

```

Call:
ergm(formula = network_Full5yr_All ~ edges + nodematch("College",
  diff = TRUE) + nodemix("prop_quartile"))

Maximum Likelihood Results:

Estimate Std. Error MCMC % z value Pr(>|z|)
edges -6.36378 0.16042 0 -39.669 < 1e-04 ***
nodematch.College.Arts_&_Sciences 1.38604 0.08585 0 16.144 < 1e-04 ***
nodematch.College.Business_&_Economics 3.65164 0.29633 0 12.323 < 1e-04 ***
nodematch.College.Education 2.58721 0.10211 0 25.337 < 1e-04 ***
nodematch.College.Engineering 1.85438 0.07450 0 24.890 < 1e-04 ***
nodematch.College.Health_Sciences 2.73266 0.19314 0 14.149 < 1e-04 ***
nodematch.College.Innovation_and_Design 3.15790 0.78914 0 4.002 < 1e-04 ***
nodematch.College.Other 1.88623 0.17566 0 10.738 < 1e-04 ***
nodematch.College.School_of_Public_Service 3.10759 0.27846 0 11.160 < 1e-04 ***
mix.prop_quartile.1.2 -0.13526 0.22899 0 -0.591 0.55474
mix.prop_quartile.2.2 0.34555 0.32115 0 1.076 0.28194
mix.prop_quartile.1.3 -0.03501 0.20550 0 -0.170 0.86474
mix.prop_quartile.2.3 0.91006 0.19833 0 4.589 < 1e-04 ***
mix.prop_quartile.3.3 1.29840 0.19526 0 6.650 < 1e-04 ***
mix.prop_quartile.1.4 0.51960 0.18533 0 2.804 0.00505 **
mix.prop_quartile.2.4 1.35987 0.18440 0 7.375 < 1e-04 ***
mix.prop_quartile.3.4 2.08274 0.16661 0 12.500 < 1e-04 ***
mix.prop_quartile.4.4 2.92366 0.16670 0 17.539 < 1e-04 ***

---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Null Deviance: 137569 on 99235 degrees of freedom
Residual Deviance: 11101 on 99217 degrees of freedom

AIC: 11137 BIC: 11308 (Smaller is better. MC Std. Err. = 0)

```

Figure F.3: Edges, Nodematch, and Nodemix ERGM Summary

```

call:
ergm(formula = network_Full5yr_All ~ edges + nodemix("prop_quartile") +
    nodefactor("college") + nodematch("college", diff = TRUE) +
    gwdegree(0.35, T) + gwesp(0.35, T), eval.loglik = T, control = control.ergm(MCMC.samplesize = 10000,
    MCMC.burnin = 1e+05, MCMC.interval = 1000, seed = 567), verbose = T)

Monte Carlo Maximum Likelihood Results:

      Estimate Std. Error MCMC % z value Pr(>|z|)
edges          -10.48366  0.35038   0 -29.921 < 1e-04 ***
mix.prop_quartile.1.2  0.52340  0.25707   0  2.036  0.041745 *
mix.prop_quartile.2.2  1.31860  0.38993   0  3.382  0.000721 ***
mix.prop_quartile.1.3  0.72794  0.23769   0  3.062  0.002195 **
mix.prop_quartile.2.3  1.85877  0.30258   0  6.143 < 1e-04 ***
mix.prop_quartile.3.3  2.04987  0.30113   0  6.807 < 1e-04 ***
mix.prop_quartile.1.4  0.98916  0.22114   0  4.473 < 1e-04 ***
mix.prop_quartile.2.4  1.86755  0.29141   0  6.409 < 1e-04 ***
mix.prop_quartile.3.4  2.29764  0.28886   0  7.954 < 1e-04 ***
mix.prop_quartile.4.4  2.54906  0.28873   0  8.829 < 1e-04 ***
nodefactor.college.Business_&_Economics  0.10104  0.12144   0  0.832  0.405432
nodefactor.college.Education      -0.07747  0.07522   0 -1.030  0.303026
nodefactor.college.Engineering     -0.02210  0.07671   0 -0.288  0.773260
nodefactor.college.Health_Sciences -0.18579  0.13340   0 -1.393  0.163718
nodefactor.college.Innovation_and_Design 0.34428  0.11452   0  3.006  0.002645 **
nodefactor.college.other         0.33685  0.07442   0  4.526 < 1e-04 ***
nodefactor.college.School_of_Public_Service 0.05614  0.11376   0  0.494  0.621637
nodematch.college.Arts_&_Sciences  0.87990  0.10537   0  8.350 < 1e-04 ***
nodematch.college.Business_&_Economics 2.08352  0.23722   0  8.783 < 1e-04 ***
nodematch.college.Education        1.57093  0.12385   0 12.684 < 1e-04 ***
nodematch.college.Engineering      0.96073  0.10108   0  9.505 < 1e-04 ***
nodematch.college.Health_Sciences 2.03462  0.22102   0  9.206 < 1e-04 ***
nodematch.college.Innovation_and_Design 1.84795  0.57158   0  3.233  0.001225 **
nodematch.college.other          0.68457  0.17487   0  3.915 < 1e-04 ***
nodematch.college.School_of_Public_Service 1.92168  0.21775   0  8.825 < 1e-04 ***
gwdeg.fixed.0.35            3.86187  0.31135   0 12.403 < 1e-04 ***
gwesp.fixed.0.35           3.28750  0.10425   0 31.535 < 1e-04 ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Null Deviance: 137569  on 99235  degrees of freedom
Residual Deviance:  8728  on 99208  degrees of freedom

AIC: 8782  BIC: 9038  (Smaller is better. MC Std. Err. = 0.7134)

```

Figure F.4: Geometrically Weighted Terms Only ERGM Summary

```

call:
ergm(formula = network_Full5yr_All ~ edges + nodemix("prop_quartile") +
    nodefactor("college") + nodematch("college", diff = TRUE) +
    gwdegree(0.35, T) + gwesp(0.35, T), eval.loglik = T, control = control.ergm(MCMC.samplesize = 10000,
    MCMC.burnin = 1e+05, MCMC.interval = 1000, seed = 567), verbose = T)

Monte Carlo Maximum Likelihood Results:

      Estimate Std. Error MCMC % z value Pr(>|z|)
edges          -10.48366  0.35038   0 -29.921 < 1e-04 ***
mix.prop_quartile.1.2  0.52340  0.25707   0  2.036  0.041745 *
mix.prop_quartile.2.2  1.31860  0.38993   0  3.382  0.000721 ***
mix.prop_quartile.1.3  0.72794  0.23769   0  3.062  0.002195 **
mix.prop_quartile.2.3  1.85877  0.30258   0  6.143 < 1e-04 ***
mix.prop_quartile.3.3  2.04987  0.30113   0  6.807 < 1e-04 ***
mix.prop_quartile.1.4  0.98916  0.22114   0  4.473 < 1e-04 ***
mix.prop_quartile.2.4  1.86755  0.29141   0  6.409 < 1e-04 ***
mix.prop_quartile.3.4  2.29764  0.28886   0  7.954 < 1e-04 ***
mix.prop_quartile.4.4  2.54906  0.28873   0  8.829 < 1e-04 ***
nodefactor.College.Business_&_Economics  0.10104  0.12144   0  0.832  0.405432
nodefactor.College.Education      -0.07747  0.07522   0 -1.030  0.303026
nodefactor.College.Engineering     -0.02210  0.07671   0 -0.288  0.773260
nodefactor.College.Health_Sciences -0.18579  0.13340   0 -1.393  0.163718
nodefactor.College.Innovation_and_Design  0.34428  0.11452   0  3.006  0.002645 **
nodefactor.College.other        0.33685  0.07442   0  4.526 < 1e-04 ***
nodefactor.College.School_of_Public_Service  0.05614  0.11376   0  0.494  0.621637
nodematch.college.Arts_&_Sciences  0.87990  0.10537   0  8.350 < 1e-04 ***
nodematch.college.Business_&_Economics  2.08352  0.23722   0  8.783 < 1e-04 ***
nodematch.college.Education       1.57093  0.12385   0 12.684 < 1e-04 ***
nodematch.college.Engineering      0.96073  0.10108   0  9.505 < 1e-04 ***
nodematch.college.Health_Sciences  2.03462  0.22102   0  9.206 < 1e-04 ***
nodematch.college.Innovation_and_Design  1.84795  0.57158   0  3.233  0.001225 **
nodematch.college.other         0.68457  0.17487   0  3.915 < 1e-04 ***
nodematch.college.School_of_Public_Service  1.92168  0.21775   0  8.825 < 1e-04 ***
gwdeg.fixed.0.35            3.86187  0.31135   0 12.403 < 1e-04 ***
gwesp.fixed.0.35           3.28750  0.10425   0 31.535 < 1e-04 ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Null Deviance: 137569  on 99235  degrees of freedom
Residual Deviance:  8728  on 99208  degrees of freedom

AIC: 8782  BIC: 9038  (smaller is better. MC Std. Err. = 0.7134)

```

Figure F.5: Selected Model Summary

## APPENDIX G: LOVE NETWORK INTERACTIONS

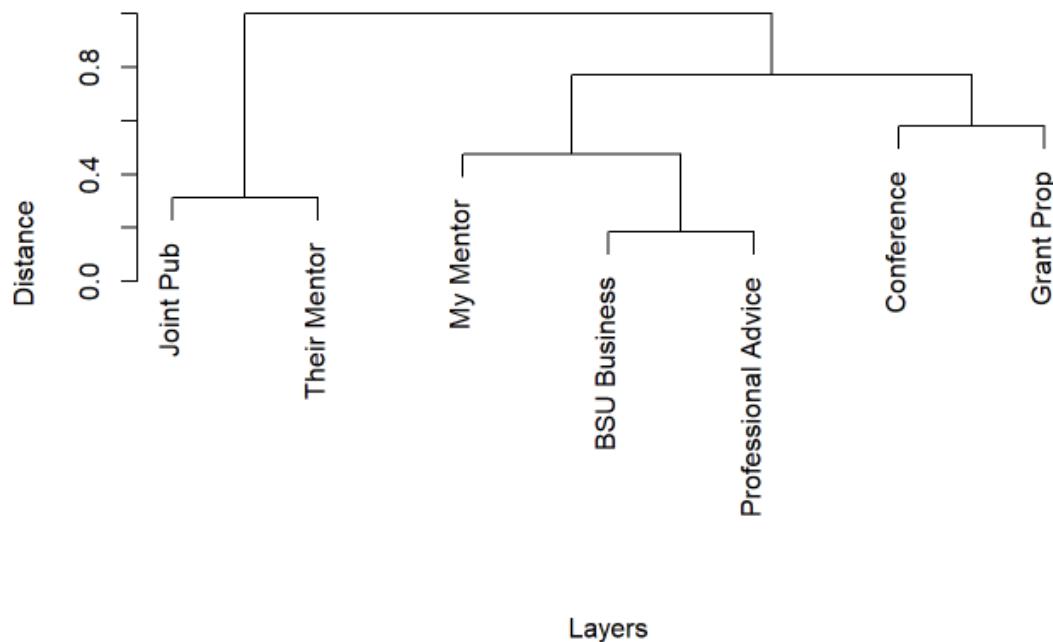


Figure G.1: Dendrogram representing the hierarchical clustering based on Jensen-Shannon divergence values within the ‘Professional’ network of Team J, showcasing the progressive aggregation of network layers.

|               | Joint Pub | Conference | Aggregation 1 | Grant Prop | My Mentor | Their Mentor |
|---------------|-----------|------------|---------------|------------|-----------|--------------|
| Joint Pub     | 0.0000    | 1.0000     | 1.0000        | 1.0000     | 1.0000    | 0.3113       |
| Conference    | 1.0000    | 0.0000     | 0.5820        | 0.5803     | 0.7704    | 1.0000       |
| Aggregation 1 | 1.0000    | 0.5820     | 0.0000        | 0.4662     | 0.3944    | 0.9028       |
| Grant Prop    | 1.0000    | 0.5803     | 0.4662        | 0.0000     | 0.6918    | 1.0000       |
| My Mentor     | 1.0000    | 0.7704     | 0.3944        | 0.6918     | 0.0000    | 1.0000       |
| Their Mentor  | 0.3113    | 1.0000     | 0.9028        | 1.0000     | 1.0000    | 0.0000       |

**Table G.1:** Jensen-Shannon Distance Matrix for Professional Aggregation 1

|               | Conference | Aggregation 1 | Grant Prop | My Mentor | Aggregation 2 |
|---------------|------------|---------------|------------|-----------|---------------|
| Conference    | 0.0000     | 0.5820        | 0.5803     | 0.7704    | 1.0000        |
| Aggregation 1 | 0.5820     | 0.0000        | 0.4662     | 0.3944    | 0.9131        |
| Grant Prop    | 0.5803     | 0.4662        | 0.0000     | 0.6918    | 1.0000        |
| My Mentor     | 0.7704     | 0.3944        | 0.6918     | 0.0000    | 1.0000        |
| Aggregation 2 | 1.0000     | 0.9131        | 1.0000     | 1.0000    | 0.0000        |

**Table G.2:** Jensen-Shannon Distance Matrix for Professional Aggregation 2

|               | Conference | Aggregation 3 | Grant Prop | Aggregation 2 |
|---------------|------------|---------------|------------|---------------|
| Conference    | 0.0000     | 0.5970        | 0.5803     | 1.0000        |
| Aggregation 3 | 0.5970     | 0.0000        | 0.4718     | 0.9248        |
| Grant Prop    | 0.5803     | 0.4718        | 0.0000     | 1.0000        |
| Aggregation 2 | 1.0000     | 0.9248        | 1.0000     | 0.0000        |

**Table G.3:** Jensen-Shannon Distance Matrix for Professional Aggregation 3

|               | Conference | Aggregation 4 | Aggregation 2 |
|---------------|------------|---------------|---------------|
| Conference    | 0.0000     | 0.5786        | 1.0000        |
| Aggregation 4 | 0.5786     | 0.0000        | 0.9346        |
| Aggregation 2 | 1.0000     | 0.9346        | 0.0000        |

**Table G.4:** Jensen-Shannon Distance Matrix for Professional Aggregation 4

|                      | Aggregation 5 |
|----------------------|---------------|
| Aggregation 2        | 0.9379861     |
| Aggregation 1        | 1.093113      |
| Aggregation 0        | 1.217644      |
| Aggregation Complete | 2.267439      |

**Table G.5:** Jensen-Shannon Distance Matrix for Professional Aggregation 5

| Layer Aggregation    | Mean Relative Entropy Values |
|----------------------|------------------------------|
| Aggregation 0        | 1.217644                     |
| Aggregation 1        | 1.093113                     |
| Aggregation 2        | 1.295395                     |
| Aggregation 3        | 1.186167                     |
| Aggregation 4        | 0.966777                     |
| Aggregation 5        | 1.439195                     |
| Aggregation Complete | 2.267439                     |

**Table G.6:** Von Neumann Entropy for Multilayered “Professional” Networks