Expanding the Network Evaluation Toolkit:

Combining Social Network Analysis & Qualitative Comparative Analysis

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ABSTRACT

Social networks are complex systems of interrelated individuals or groups. This research focuses on evaluation of social networks that come together for a common social change purpose, called collective action networks (Ernstson, 2011). Researchers have used social network analysis (SNA) to examine the relationship structures and characteristics of collective action networks. However, determining whether collective action networking produces outcomes has been challenging because networks are complex, affected by context, and produce interdependent data. I address these challenges by pairing SNA with qualitative comparative analysis (QCA), a configurational comparative method. Using QCA, researchers can tease out which conditions are necessary or sufficient to produce an outcome. I describe networks and then SNA and QCA, including the advantages and limitations of each method. Then, using data from a case network of community-based resource management groups in Hawaii, I analyze the social network. I then analyze the same network using an explanatory mixed methods case study. These analyses produce the data needed for QCA. I use QCA to integrate the quantitative SNA data with qualitative data to determine what conditions are necessary and sufficient for the network's desired outcome. Finally, I compare the results from SNA alone to the results of QCA with SNA to determine what the use of QCA can add to an understanding of how networking contributes to achieving outcomes.

KEYWORDS: Network, network evaluation, collective action network, social network analysis, qualitative comparative analysis, community-based resource management

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CHAPTER ONE: INTRODUCTION

As co-founder and director of a nonprofit organization, I wanted to know whether the work into which we were pouring time and resources was producing the intended social changes. Our organization theory of change was founded in collective action networking. That theory is that bringing together people and organizations to address desired social change would produce better results than was possible when working in isolation (Ernstson, 2011; Holley, 2012; Kania & Kramer, 2011; Ostrom, 2009; Plastrik et al., 2014). The drive to discover whether collective action networking produced better results led me to the field of evaluation, in which I have specialized since 2012. Through those years, I have continued to try to answer the core question of whether networking produces desired outcomes. What I thought would be a straightforward search has taken me on an archeological dig through research methods. I have learned that I am not alone in this search to discover the appropriate methods to answer the question of whether networking produces desired outcomes. The field of evaluation has suffered from a lack of methodological clarity about how to evaluate networks.

In this chapter, I present the crux and significance of the problem affecting network evaluation. I explore prior literature to describe the key concepts related to the problem, the developmental progression of my understanding of the problem, and the gaps in the literature. I conclude this chapter with how the information explored herein has led to the purpose and key questions under investigation in this study and, therefore, how this study can contribute to the knowledge base for several audiences.

Description of Research Problem

Nonprofit organizations, government agencies, and foundations are investing heavily in collective action networking, which may be framed as networking, collaborating, coalition-building, collective impact, or similar terms (Brown et al., 2020; Varda & Sprong, 2020). For example, the National Skills Coalition created Skills2Compete as state-based coalitions to increase workforce development opportunities and outcomes. State coalitions engage cross-sectoral partners such as funders, lawmakers, educational institutions, community-based organizations, and businesses with a common goal to improve job preparedness for adults (Leung, 2016). These networked approaches have become more common over the past 30 years and have been called "the norm to address public health and social problems" (Wolf et al., 2020, p. 9); "a mainstay of community-based health promotion efforts" (Kegler et al., 2020, p. 140); and even a "best practice in solving complex problems" (Varda & Sprong, 2020, p. 67).

The purpose of investing in collective action networking is to increase opportunities for social change while reducing barriers through sharing information, increasing efficiency, limiting redundancy, improving policy and practice, and targeting support and funding from multiple sources to the same issue (Kania & Kramer, 2011; Plastik et al, 2014). Through working together, network partners are supposed to find and implement solutions to persistent, wicked problems that they would not be able to solve on their own. Wicked problems are complex, evolving, and seemingly entrenched, with multiple layers of overlapping problems and subproblems that people define and understand differently (Weber & Khademian, 2008). Poverty, climate change, and racism are wicked problems, for example. Wicked problems often have been defined by their complexity:

> The social and political complexity associated with such problems can be overwhelming. Participants or stakeholders in the problem are numerous, with a variety of worldviews, political agendas, educational and professional backgrounds, programmatic responsibilities, and cultural traditions. And the participants come and go depending on

the way in which a wicked problem affects individuals, organizations, or groups of people at any given point in time. (Weber & Khademian, 2008, p. 336)

Because of the complexity of wicked problems, the results of efforts by collective action networks to tackle them are murky despite the investment by nonprofit organizations, government agencies, and foundations. Cabaj and Weaver (2016), in an article reviewing the state of collective impact, concluded, “The jury is still out on the ability of [collective impact] efforts to generate deep, wide, sustained impact on tough societal challenges” (p. 12). In a literature review about coalition evaluation, authors sought attributable outcomes in 55 articles and concluded, “The same challenges which limited the field a decade ago remain…with limited to no examination of how the coalition(s) influenced program effectiveness” (Kegler et al., 2020). Given the urgency and importance to people’s lives to reduce the grip of wicked problems, along with the investment in collective action networking to do just that, one might expect a more robust connection between networking and the desired social change outcomes.

Why is the connection between collective action networking and social change outcomes elusive? To make the connection would require an understanding of the collective action network, an understanding of the outcomes, and an understanding of links between them. Just as wicked problems are complex, collective action networks are complex. Evaluating them is complicated, as many authors in a coalitions-focused issue of *New Directions for Evaluation* acknowledged (Brown et al., 2020; Hilgendorf et al., 2020; Kegler et al., 2020; Price et al., 2020; Stachowiak et al., 2020; Varda & Sprong, 2020). Just like wicked problems, network scenarios are complex and affected by shifting contexts (Carolan, 2014; Ernstson, 2011).

Complexity in network scenarios affects the research methods that evaluators can use to study them. In my own search to establish whether networking makes a difference, I learned that

I could not use inferential statistical approaches for the network contexts in which I worked. The networks were small, and the data were interdependent—both characteristics that would have led to questionable results from inferential statistical analyses (Carolan, 2014). Qualitative methods were more useful but did not result in a causal link from networking to outcomes that was clear enough for some audiences including funders. Social network analysis (SNA) was tailor-made for research about networks and complexity. SNA produces information about the structures and patterns of interconnectivity within an interrelated group (Borgatti & Halgin, 2011). Neither small sample sizes nor interdependency present a problem for SNA. Using SNA, I gained clarity about whether networking was increasing connectivity. Unfortunately, SNA could not help to answer the question about whether that increased connectivity was important to producing the desired outcomes.

I had almost given up when I learned about a method with which small and medium sample sizes could be used in complex situations. Qualitative comparative analysis (QCA) is a case-based research method rooted in mathematical set theory, Boolean algebra, and the logic of agreement and difference (Ragin, 1987). Ragin (1987) developed QCA to unravel causal complexity and accommodate both qualitative and quantitative data. The result of analysis with QCA is a causal pathway that identifies the conditions that are necessary and sufficient to produce an outcome (Ragin, 1987; Ragin 2005). This study will explore the methodological question of whether pairing QCA with SNA can move further than SNA alone in establishing a link between networking and outcomes for collective action networks.

Review of Relevant Scholarship

Given the collective action networking context and the complexity of typical network scenarios, this study will be grounded in both (1) collective action theory and (2) systems and complexity theory. Collective action theory will provide framing for the situational context, meaning that the research questions, data collected, and results will both reflect and contribute to the established knowledge about collective action. Systems and complexity theory will provide framing for the methodological context, meaning that the research methods, questions, and approaches will be appropriate given what is understood about complex systems. SNA and QCA, as the foci for this study, have been established as acceptable methods to study complex systems (Borgatti et al., 2009; Mello, 2020). The relevant scholarship for these four study elements of collective action theory, systems and complexity theory, SNA, and QCA is described below.

Collective Action Theory

Prior research about collective action theory has provided a definition and variables of collective action. Collective action theory addresses the behavior of individuals in interdependent situations (Ostrom, 2009). While some have hypothesized that individuals in such situations will behave in ways that prioritize their own interests over the collective interests of a group, even to their long-term detriment, others have pointed to real-life situations in which people have self-organized for mutual benefit (Kim & Bearman, 1997; Ostrom, 1990, 2009). Collective action theorists have worked to uncover the variables that distinguish between self-interested behaviors and mutually beneficial behaviors. While research continues, some of the variables identified have been the structure of connectivity between group members, whether individuals are compelled to participate, historical actions, face-to-face communication, the nature of the collective benefit, who bears the costs of collective action toward a common benefit, a sense of personal contribution to a collective benefit, and the number and heterogeneity of individuals (Ostrom, 2009).

Collective action networks come together to affect social change. Collective action theorists hypothesize that, depending on the variables above, participants in a network may contribute, "free-ride" or cheat, or opt out entirely (Ostrom, 2009, p. 6). But Kim and Bearman (1997) argued that the free-ride element of collective action theory ignored a key network dynamic, which is that networks raise participants' consciousness and build consensus that spurs participants to trust and action (also Kim, 2018). So, when evaluating networks through a collective action theory lens, one should consider the role of trust, consciousness-building, and consensus-building in addition to Ostrom's (2009) named variables. It has been suggested that some of these variables can be described using SNA; specifically, networks with greater density, degree centralization, and multiplexity are more likely to engage in collective action (Crossley & Ibrahim, 2012).

Systems and Complexity Theory

While collective action theory provides framing for the "what" (a network), systems and complexity theory provides framing for the "how" (methods). The research methods must be appropriate to the context. In this case, the context is a system including boundaries and links. A system is a bounded set of parts and the links between those parts (Hummelbrunner, 2011). Collective action networks are bound by the collective action motivating the network. The parts are the participants of the network, whether they are individuals, groups, and/or organizations. The links are the relationships between them. The participants share common interests or functions that also are interrelated and comprised of nested layers (Jolley, 2014; Walton, 2014). The participants also affect the system itself and the other parts of the system, which creates a co-evolutionary dynamic (Walton, 2016).

Hummelbrunner (2011) described the characteristics of links in a system. For a network, understanding the relationships between participants requires considering the purpose for the different relationships in the system, including for the network overall and for each link in the network. Power dynamics affect all the actual and possible links, including the boundary of who is included in the system and who is kept out.

Evaluating a system is complex. Considering the characteristics of a system, evaluators must investigate the parts of the system, the amalgam, the patterns of interaction, the role and effects of power, and the feedback effects throughout the system. They must do this within a context that is emergent, adaptive, unpredictable, dynamic, and nonlinear (Hummelbrunner, 2011; Jolley, 2014; Walton, 2014). Evaluation has borrowed elements of theory from the fields of economics, sociology, psychology, ecology, technology, and more to develop evaluation approaches appropriate for complex systems. Systems thinking and complexity science, also called complex adaptive systems or the complexity of systems, have been adapted for evaluation from these other fields (Gates, 2016; Walton, 2016). Although the evaluation of complex systems has been receiving increased attention (Gates, 2016; Walton, 2014; Walton, 2016), a singular approach to this evaluation context has been elusive (Walton, 2014). What is clear is that complexity affects every step of an evaluation (Gates, 2016; Walton, 2016).

Hummelbrunner (2011) suggested that evaluators approach the evaluation of complex systems by thinking systematically rather than using a stepwise set of rules or actions: “Thinking systemically is about making sense of the world rather than merely describing it, a sense-making process that organizes the messiness of the real world into concepts and components that allow us to understand better” (p. 397). Cabrera et al. (2008), Hummelbrunner (2011), and Walton

(2014) contributed suggestions on how evaluators should go about that process of "sense-making," which are combined and summarized here:

- Defining the boundaries, level, and unit of analysis of a system
- Describing the context in which the system exists
- Describing the interrelationships present in the system, including who benefits and how, who controls resources and how, who makes decisions and how, and what expertise is valued or ignored
- Describing the distinctiveness of interrelationships, including both what they are and what they are not
- Unpacking motivations, behaviors, values, and feedback effects throughout the system
- Using participatory methods to understand participant perspectives
- Using case study and comparison designs
- Using mixed methods and multiple methods (also Kallemeyn et al., 2020)
- Attending to evaluation timing because systems are nonlinear. Identifying discreet variables and parsing out attribution in such conditions is challenging, at least in part because the nonlinear nature of systems confounds temporal precedence (Jolley, 2014; Kallemeyn et al., 2020; Mowles, 2014).
- Framing evaluation in social science theory to help "organize the messiness" (Hummelbrunner, 2011, p. 397)

These suggestions are not a prescriptive approach to evaluation using systems and complexity theory, but they provide guidance on how to operationalize systems and complexity theory in research and evaluation practice. Using systems and complexity theory as the methodological frame will add clarity about the research methods, questions, and approaches I will use in this study. I turn next to two methodological approaches, SNA and QCA, that others have found useful in evaluating complex systems.

Social Network Analysis

My own search for evidence about the effectiveness of collective action networking led me to SNA, which offers multiple benefits to network evaluation but falls short of answering the question about the outcomes networking produces. SNA has been cited as a method appropriate for complex contexts, and it is tailor-made for collective action networks (Gates, 2016; Kallemeyn et al., 2020; Varda & Sprong, 2020; Walton, 2014). The unique contribution of SNA is that it provides an understanding of the structures and patterns of relationships within a system (Bodin & Prell, 2011; Borgatti & Foster, 2003; Brandes et al., 2013; Durland & Fredericks, 2005; Lawlor & Neal, 2016). I have used SNA to better understand the structures of networks and the effectiveness of different networking strategies (e.g., gatherings, workshops, site visits, communication) toward increasing connectivity. Unfortunately, SNA could not help me understand networking outcomes about factors other than relationship structures and patterns. Connectivity in a network may have increased, but to what end?

Some researchers have attempted to use SNA to link networking to non-relational outcomes, but their use of SNA data is questionable. Some have used SNA data as independent variables for inferential quantitative approaches to research and outcome evaluations, which may appear to be a logical solution (Daly et al., 2013; Kegler et al., 2020; Maglajlic & Helic, 2012; Popeier, 2018). Importantly, the interdependence of the SNA data may create instability in some inferential models (Bodin et al., 2017; Brandes et al., 2013; Carolan, 2014; Chung et al., 2008; Fredericks & Durland, 2005; Hollstein, 2014; Popeier, 2018). Also, the most common inferential statistical procedures such as regression, correlation, and ANOVA were developed from probability theory and are meant to be employed when random sampling is utilized. Random sampling typically is not used in evaluations involving SNA (Carolan, 2014). Using SNA data with traditional inferential statistics is a practice researchers avoid when they care about the accuracy of the results.

Other researchers have combined SNA and qualitative data, which has produced interesting results but still falls short of establishing a link between networking and non-relational outcomes. In these studies, SNA helped to tell the story of relationship structures and patterns, while qualitative data from interviews, documents, focus groups, and/or observations added context and meaning (Berthod et al., 2017; Bodin et al., 2017; Cvitanovic et al., 2017; Maglajlic & Helic, 2012; Marshall & Staeheli, 2015; Martínez et al., 2003; Pitts & Spillane, 2009; Sandström & Carlsson, 2008). Several authors discussed challenges with their studies due to complexity and results that were not as enlightening as they had hoped. For example, in a study combining ethnographic methods with SNA, the authors concluded that interorganizational networks "are still in need of an appropriate research methodology" and urged future researchers to continue mixed methods research with SNA and ethnography or other qualitative methods (Berthod et al., 2017, p. 315). Similarly, Bodin et al. (2017) were confounded by what they described as an "entanglement of cause-and-effect pathways" that were further complicated by "a substantial amount of 'noise,' which further amplifies the need for more empirical research" (pp. 309-310). Although SNA has been useful in revealing relationship structures and patterns, it has not conclusively helped researchers or evaluators establish a link between those relationships and non-relational outcomes. Evaluators and researchers may be able to use QCA to fill this analytical gap.

Qualitative Comparative Analysis

QCA is a promising method with several benefits to untangle the methodological conundrum of how to link networking to outcomes, based on the purpose for which QCA was created and the results it produces. Ragin (1987) developed QCA to be used in situations where “causal complexity” frustrated traditional inferential statistical approaches (Mello, 2020, p. 1). Causal complexity refers to complex situations in which there are multiple pathways to an outcome or combinations of conditions that might contribute to an outcome (Mello, 2020). Using data from multiple cases that have achieved a certain outcome to varying degrees, the analysis teases out which conditions those successful cases had in common (Kahwati & Kane, 2020). Hypothetically, I should be able to enter into a QCA algorithm various conditions including SNA data to determine whether connectivity from networking is linked with a desired outcome.

That hypothetical result of connecting networking and outcomes is the primary benefit of QCA in a network evaluation context. QCA does not suffer the same constraints regarding sample sizes and data independence that inferential statistics approaches do (Kahwati & Kane, 2020). Whereas traditional inferential statistical tests utilize linear algebra, QCA utilizes Boolean algebra, mathematical set theory, and the logic of agreement and difference. Nor does QCA require random sampling, again because it does not involve inferential statistics, which are derived from probability theory. Sample sizes and random sampling also are not an issue because the purpose of QCA is not to statistically generalize to a population but to explain the conditions that were necessary or sufficient for an outcome. Nor is QCA constrained to a single method or type of data; it works with both quantitative and qualitative data.

This study will focus specifically on the methodological combination of SNA and QCA, as compared with SNA alone. From this study, I hope to add a methodological approach to evaluators' toolbox that will produce more robust information about the value of collective action networking.

Gaps in the Literature

QCA has been used in many fields, including evaluation, but has not often been paired with SNA. While English-language evaluation journals have published a handful of articles about QCA, the most significant contribution came in 2020 with Kahwati and Kane's book about using QCA for mixed methods research and evaluation. The authors incorporated throughout the book many examples of evaluations and research that used QCA, but QCA was never used with SNA. In a review of methods used to evaluate the effectiveness of coalitions, Kegler et al. (2020) found that SNA, quasi-experimental design, case study, multiple case study, cross-sectional study, and others had been utilized. The authors did not mention studies using QCA.

I found three prior studies that paired comparative case studies with SNA (Bodin et al., 2017; Sandström & Carlsson, 2008; Velastegui, 2013). Only Velastegui (2013) utilized QCA and SNA, though she did not ask an evaluative, outcomes-oriented question. Rather, she was interested in whether teachers' structural positions in a network were causally linked to their leadership and influence. These examples hinted that SNA is methodologically compatible with QCA. None of the studies combined SNA and QCA to answer an outcomes-oriented evaluation question, and they did not answer the question of how networking contributes to outcomes.

Study Objectives

The purpose of this study is to discover whether combining SNA with QCA produces more informative results, when compared with SNA alone, about how collective action networking contributes to desired outcomes. For the purposes of this study, I use the word "contribute" in the context of the field of evaluation. For evaluators, contribution is a determination of whether certain activities *helped to* cause the observed outcomes, as opposed to attribution, which implies that activities were shown to cause the outcomes (Almquist, 2011). In the case of collective action networking, I am trying to determine whether networking contributed to, or played a role in, groups achieving outcomes, recognizing that other activities and circumstances also may have contributed to, or played a role in, groups achieving those outcomes.

For this research, I will use a series of three scaffolded studies. In the first study, I will use a quantitative, descriptive, nonexperimental design focusing on the structures and relationship characteristics of a network. In the second study, I will use an explanatory mixed methods case study. The quantitative data from Study 1 will stand as the initial quantitative strand for the mixed methods case study. I will use information from the quantitative strand to inform the development of an interview protocol and interviewee list for the qualitative strand. Qualitative data, including interviews and archival documents, will provide context and explanation for the quantitative results. I will use QCA to integrate the quantitative (including SNA) and qualitative data, teasing out the conditions that are necessary or sufficient to achieve network outcomes. Finally, the third study will feature a comparison of Study 1, the quantitative study using SNA, to Study 2, the explanatory mixed methods case study using QCA with SNA. Through these three scaffolded studies, I will answer the research questions below.

Research Questions

Based on the problem and gaps in the literature, the research questions guiding this study are as follows:

<u>Study 1: Social Network Analysis</u>

- To what degree are various network structures and relationship characteristics present for the E Alu Pū network and member groups?
- To what degree have intended outcomes been achieved by the E Alu Pū network and member groups?

Study 2: Quantitative Comparative Analysis

- For the E Alu Pū network, what intended and unintended outcomes emerge from networking experiences and activities?
- For the E Alu Pū network, what conditions are necessary and sufficient to achieve the intended outcomes?
- How does qualitative data about the E Alu Pū network help to explain or contextualize quantitative survey data about network relationships, structures, and outcomes?

Study 3: Comparison of Findings from Study 1 with Findings from Study 2

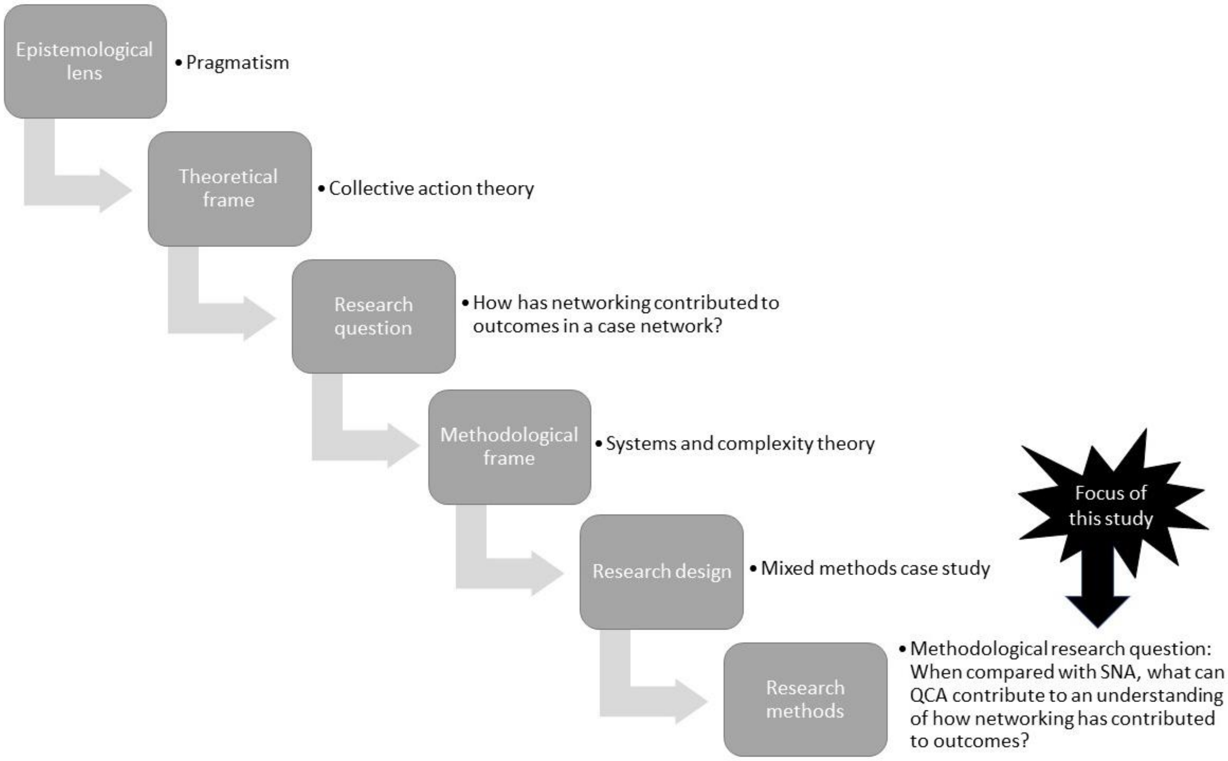
- When compared with using SNA alone, what additional understanding about networking outcomes can be gained by using QCA with SNA?

The study is driven by the overarching methodological research question about the possible contribution of QCA to evaluation of collective action networks. By conducting the first study that focuses on network characteristics and relationships, I will be able to evaluate a network using standard survey techniques with SNA results. By conducting the second study that provides context and explanation for the case, I will gather the case data required for QCA and will conclude the mixed methods study by using QCA to integrate the quantitative and qualitative data. By conducting a comparison of Study 1 to Study 2, I will be able to compare the results I gleaned using only SNA to the results I gleaned using QCA with SNA. Comparing the two sets of findings will answer the question of what additional understanding about networking outcomes I can produce by using QCA with SNA.

Figure 1 summarizes the problem described in this chapter and how it has led to the question at hand. The overall epistemological lens for this study is pragmatism, a pluralistic worldview that emphasizes the research question as opposed to methods and welcomes all types of data to help answer the question (Creswell & Plano Clark, 2018). The problem is situated within the theoretical frame of collective action theory. The initial question I set out to answer as a nonprofit co-founder and director was whether networking contributed to outcomes. In selecting the research methods to use to answer the question, I considered systems and complexity theory. Based on the inherent complexity of the research scenario, I chose explanatory mixed methods case study as the research design. This design uses both quantitative and qualitative data to examine the case of a specific network. To answer the question about how networking has contributed to outcomes, I will need to understand the network, the outcomes, and any link between the two. I will use SNA to examine the network and quantitative and qualitative data to examine the outcomes. How to link the two effectively and with methodological integrity remains a question. The focus of this study is whether QCA can produce additional understanding about the outcomes of collective action networking.

Figure 1

Path from Problem to Methodological Research Question



Contribution of the Study

This study will contribute to the knowledge base for five audiences: the case network and its stakeholders, evaluators (both practitioners and researchers), network facilitators and funders, network scientists, and mixed methods researchers. First, the case network under consideration for this study, E Alu Pū, will benefit from the results about networking and outcomes. The study will provide an opportunity for the network coordinator and facilitating organization, network member groups, funders, partners, and other stakeholders to learn about how the networking strategy has affected member groups and conditions within its context. The results will become part of the network's story while raising opportunities for improvement.

Second, the tools and models available to evaluators for network evaluation are not sufficient to address the key evaluation question of merit determination. Evaluators have been using methods improperly or doing the best we can with the models available. This research has the potential to introduce a new, better approach to network evaluation for the evaluators' toolkit.

Third, network facilitators and funders invest in a networking model because they believe it will produce better results than non-networking models. Because data about networks is complex and taken from a small number of interdependent observations, there is a dearth of rigorous, credible evaluation to support such considerable investment in networks. This study will result in findings about whether networking contributed to outcomes in a case network, and it will provide a possible method to affirm whether the investment in networks is supported by the evidence.

Fourth, the study will build upon the research base about the different dimensions of networks. QCA will add another layer of empirical integrity to the interpretation of SNA data, which will inform the structuralism-versus-connectivism debate and may continue to push SNA from its use as a data analysis tool toward its use as a social science method.

Fifth, the study will interest mixed methods researchers. The defining characteristic of a mixed methods study is the integration of quantitative and qualitative data (Creswell & Plano Clark, 2018). This study will provide evidence about whether using QCA as an integration tool is an effective, advisable method. Because this study combines two methods in a new way for a new purpose, it has the potential to contribute to the knowledge base of these multiple audiences.

Chapter One Summary

Partners in collective action networking need to know whether they are contributing to the change they were created to produce. Even more, they need to know what they are doing that is contributing to change and what they are doing that is not so they can focus their limited time and resources toward what works. Funders, supporters, and partners of networks need to know how to better support networks and coalitions. Networks and their funders look to evaluators to discover this information, and evaluators have tried to deliver, but we have been using methods ill-suited to the task. To establish whether QCA could be combined with SNA to answer the important question of whether networking contributes to desired social change outcomes would help evaluators provide the evidence networks need to better serve their social change goals.

CHAPTER TWO: REVIEW OF THE LITERATURE

Evaluators strive to understand the value of organizations, programs, policies, and projects, but doing so can be difficult in the increasingly complex environments in which they work (Patton, 2015). A specific case of a complex environment for evaluation is that of collective action networks, in which groups or individuals work together to solve wicked problems that are seemingly intractable, evolving, and multilayered. In this case, wicked problems lead to wicked evaluation problems (Ernstson, 2011; Weber & Khademian, 2008). These problems include the shifting contexts and stakeholders evaluators must manage, nonlinear programming with unclear beginnings and endings, varying perspectives, and complicated relationships (Hummelbrunner, 2011; Jolley, 2014; Walton, 2014). Many traditional methods used for evaluation and research cannot effectively cut through this complexity to get to the core evaluation purpose of determining merit.

To help with these wicked evaluation problems, evaluators have turned to systems and complexity theory because these interrelated theories focus on the nature of systems and change within systems (Walby, 2007). A collective action network is a system, or “a whole made up of two or more related parts,” along with the relationships between those parts (Cabrera et al., 2008, p. 302; see also Hummelbrunner, 2011). Systems theory has helped evaluators to understand which characteristics of a system to empirically observe, and complexity theory has helped evaluators to understand which characteristics of change within a system to empirically observe. Cabrera et al. (2008) analyzed systems and complexity theory and summarized key elements that evaluators should consider when evaluating complex systems:

> Any evaluand can and should be viewed in the same way that transforms contextual patterns: as parts, wholes, and the relationships among them; as well as the relationships

between the program and the larger, external forces with which it rests; distinctions must be made to set boundaries on the scope of a program and thus, establish criteria as to what can be measured to make assessments; and finally, the ability to take varied perspectives enables evaluators to better understand the richness of both a program's content and the system of which it is a part. (p. 302)

As seen in these descriptions of systems and complexity, relationships play an important role and deserve evaluators' attention (Popeier, 2018). Ignoring relationships in an evaluation—especially an evaluation of collective action networks—equates to studying an artificial environment that does not exist. Evaluators have adopted social network analysis (SNA) to understand relationships. SNA helps to reveal relational systems, the structure of relationships, the processes between participants, and the patterns revealed through those processes.

While SNA has been helpful, it does not enable evaluators to discover the key piece of information they are most interested in, which is whether the relational system and its processes contributed to outcomes or results. A possible solution to this problem is available by pairing SNA with qualitative comparative analysis (QCA), a configurational comparative method. QCA was designed for use in complex situations to determine the necessary and sufficient conditions for an outcome. If SNA and QCA are used together, evaluators may be able to determine what conditions come together to contribute to desired social change outcomes within complex environments.

What follows is a review of the most important constructs in this study. First, I describe networks and, specifically, collective action networks, which are groups that act collectively to transform society (Ernstson, 2011). I describe the different ways networks have been characterized in the literature to provide useful context when I then turn my attention to the evaluation of collective action networks. I then define SNA and review its development for the purpose of analyzing the structures and patterns of relationships in networks (Borgatti & Halgin, 2011). Then I review how SNA has been used in evaluation, including the benefits and limitations of using SNA in evaluation. I then shift the focus to QCA. I define QCA and review its development. Then I review how QCA has been used in evaluation, including the benefits and limitations of using QCA in evaluation.

The purpose of reviewing these two methods is to contribute to the toolkit evaluators have available to evaluate collective action networks within their complex contexts. Evaluators have had difficulty determining the merit of collective action networks. Using SNA has brought new insight about the structures and patterns of relationships, but evaluators cannot use SNA to determine whether networking produces desired program outcomes about factors other than relationship structures and patterns. QCA is a possible addition to the network evaluators' toolkit, enabling a determination of whether networking itself makes a difference.

Defining Networks

To begin to understand how networks can be studied, understood, and evaluated, I will first define them and then situate them within their field of study. Networks are complex systems, which affects the way researchers and evaluators study them. Within the larger body of research about systems is the study of systems that exhibit the characteristic of interrelationship (Brandes et al., 2013). Called a network, this type of system is defined broadly as one that consists of individuals or groups and the relationships between them (Borgatti & Halgin, 2011). A social network, using this broad definition, is a system of social or personal relationships such as a community of neighbors, an organization of colleagues, students in a class together, a group of friends, family members, and so on. (With the advent of web-based social networking technologies, a social network is also known as the links established through those tools—Twitter, Instagram, and Facebook, for example. Web-based social networks are not the focus of this study.)

To study a network system, researchers turn to network science, the study of relational data. Network science, the field within which SNA is seated, is a transdisciplinary field from which evaluators can bring into their work a different way of seeing. Researchers in disciplines such as management, public policy, epidemiology, ecology and conservation, education, anthropology, sociology, and more have contributed to network science (Bodin et al., 2008; Borgatti et al., 2009; Borgatti & Halgin, 2011; Brandes et al., 2013). Many of these disciplines are rooted in scientific theories that focus on the individual and generalize to a population, so network scientists have had to learn a new way of looking at things. Network science incorporates the study of individual parts or elements of a network, the relationships between those elements, and the overall structure of the network (Brandes et al., 2013). Evaluators studying networks benefit from a similar ocular shift. To understand a network is to don a multidimensional perspective that understands that the parts of a network affect each other and create feedback throughout the system.

This new way of seeing began with researchers from at least the 1930s and has continued to the present. Understanding what these network scientists discovered provides a foundation upon which network evaluators today can build. At the foundation, then, are the multiple dimensions that network scientists have used to describe networks. These include formality, level, role, and relationship, each of which I will define below. To evaluate a network, an evaluator must understand the dimensional characteristics of that particular network. With enough data from enough networks from enough disciplines, network scientists will gain an understanding of how varying degrees of the different dimensions affect other aspects of a network such as trust, efficiency, motivation, equity, and so on. By studying networks and contributing to the larger network science conversation, evaluators can contribute important information about how the different dimensions of networks affect or reflect leadership, resiliency, and adversity that can quash or buoy a social change effort.

Dimensions Along Which Networks Differ

Formality of Networks

Networks can be formal (also called "realist") or informal (also called "nominalist") (Borgatti & Halgin, 2011; Guerrero et al., 2017). Formal or realist networks have more clearly established boundaries because of deliberate grouping, while informal or nominalist networks are systems of naturally occurring relationships among people or groups without an organizing hand (Borgatti & Halgin, 2011; Guerrero et al., 2017). Consider the faculty of a traditional brick-and-mortar university as an example. The faculty comprise a formal network that is bounded not by naturally occurring relationships but by an organizing body, the university. An informal network within the same faculty might be a friendship group that forms across colleges out of a shared interest. An informal network is bounded based on the researcher's interests (Borgatti & Halgin, 2011). For example, if researchers are interested in *friendship*, they will discover a different network from researchers who are studying the same individuals but who are interested in *communication*. Each network has a unique structure and is associated with different network characteristics for individuals and for the network. By determining the boundaries of the network, an evaluator might study a formal or an informal dimension of the network.

Levels Within Networks

Within a network, researchers can study individuals, often called an "ego network," subgroups, and whole networks. Returning to the example of a university, researchers could study the *ego network* of individual faculty members and the relationships between them. Or researchers could study *subgroups* of faculty within different colleges or departments or leadership positions. Or researchers could study the *whole network* of all faculty members at the university. In order to set boundaries, researchers depend on their research questions and their perspectives on the roles of networks.

Roles of Networks

The roles of networks are debated among network scientists, with some roles widely affirmed and other roles hotly debated. What network scientists agree about is that networks affect the flow of information and knowledge (Borgatti & Halgin, 2011). For example, a highly connected department chair at a university likely will play an important role in disseminating information to their network. On the other hand, network scientists fundamentally disagree about the *action* role of networks: Some say networks act to affect outcomes, and others say networks do not affect but rather are affected by context and the actors that comprise the network (Borgatti & Foster, 2003). This is a crucial difference. Consider graduate students who decide to form a group to study together for comprehensive exams. If these students perform better on comprehensive exams, the two camps of network scientists disagree about why this group was successful. One camp of network scientists, the structuralists, assert that the act of studying *together* produced the outcome of better comprehensive exam scores. In other words, the structuralists assert that the network structure itself produced the outcome. Another camp of network scientists, the connectionists, assert that good students connected because of their shared motivation to study. In other words, the connectionists assert that the students' characteristics affected the network structure and, therefore, the outcome of better comprehensive exam scores.

Network scientists who align with the structuralist perspective believe that network theory indicates that different network structures affect outcomes with differing levels of effectiveness (Borgatti & Foster, 2003; Groce et al., 2019). However, researchers who align with the non-structuralist, connectionist perspective do not believe that it is theoretically feasible for networks to affect outcomes. These network scientists believe that the people or groups who comprise the network within a context affect both the outcomes and the network structure (Borgatti & Foster, 2003). "From a theoretical point of view, comemberships, coparticipations, geographic proximities, and trait similarities can all be seen either as dyadic factors contributing to the formation of ties (e.g., meeting the other members of your club) or as the visible outcomes of social ties (as when close friends join the same groups or spouses come to hold similar views)" (Borgatti & Halgin, 2011, p. 1170). The structuralist-connectionist debate is similar to the old chicken-and-egg question: What came first?

To provide evidence that might settle the chicken-and-egg question, the two camps, structuralists and connectionists, produce different types of studies: The connectionist camp produces studies about the causes of network structures (called theory of networks), and the structuralist camp produces studies about the consequences of networks (called network theory) (Borgatti & Foster, 2003; Borgatti & Halgin, 2011; Brandes et al., 2013; Fredericks & Durland, 2005). Evaluators should understand their own perspective and approach evaluation of networks with clarity about whether the function of networking acts to produce outcomes or whether the network is acted upon by participants and context that produce outcomes. The research questions and interpretation of data will fundamentally shift depending on the perspective. Based on collective action theory, I am approaching this study from a structuralist perspective.

Relationships Within Networks

Further complicating matters is the fact that there are different types of relationships present in any network. Borgatti and Halgin (2011) described role-based or perceptual relationships that can be described by strength, intensity, and duration. Event-based relationships, on the other hand are “discrete and transitory” relationships that can be described by the number of interactions or frequency of occurrence (p. 1170). Examples of role-based relationships within a university setting are professor-to-student, faculty member-to-faculty member, student-to-financial aid, professor-to-research area, and so on. Examples of event-based relationships within a university setting are connections between prospective students and current students on interview day, new connections between short-term university event attendees, faculty publishing with different types of journals, and so on. Different types of relationships can result in different types of networks (Borgatti & Halgin, 2011), which loops back to the prior theoretical discussion about whether networks act upon or are acted upon.

Additional research about the theory of networks and network theory is needed to build upon the foundation of our understanding of network dimensions and complexity. It is possible that additional dimensions of formality, level, role, and relationship could be defined. It is also possible that new dimensions altogether could be identified. Researchers also could address the debate in the current literature about whether networks are affected by context or affect context; new empirical evidence could indicate, as reason suggests, that both can be true.

Collective Action Networks

Now that we share an understanding of what networks are and the dimensions used to describe networks, we can attend to the specific type of network that is the focus of this study, the collective action network. Collective action networks are distinct from other types of organized groups in that the network develops formally or informally when people or groups of people come together for a common social change purpose that requires sustained effort (Christens, 2019; Holley, 2012; Plastrik et al., 2014). This type of network is called a “collective action network” because the people or groups in these networks act collectively to transform society (Ernstson, 2011). This type of network may be confused with a coalition or an organization, but these are different from a collective action network. A coalition tends to be more informal than formal, and the relationships tend to be temporary. Participants come together for a limited time, usually to advocate for a single outcome such as a policy change (Holley, 2012). On the other hand, an organization tends to be more formal, with hierarchical roles and established boundaries (Holley, 2012). Collective action networks can be distinguished from coalitions or organizations in that they exist beyond a single outcome and are sustained over a longer period. Also, their boundaries and hierarchies often are difficult to define, if not altogether absent (Holley, 2012). I will use the term “collective action network” and “network” interchangeably through the remainder of this study to describe these social change–seeking networks.

Evaluating Collective Action Networks

As established above, collective action networks serve a unique purpose, which is social change (Ernstson, 2011). Understanding this purpose is important to framing an evaluation of a collective action network. If an evaluation is meant to determine merit (Davidson, 2005), then the merit of a collective action network, arguably, is determined by whether it is producing the desired social change. To understand how the network operates to achieve its social change purpose, evaluators can describe the dimensions of the network as described above. But beyond describing the network, what tools and processes can evaluators use to determine the merit of a network? Given the complexity of networks and the still-emerging nature of network science, perhaps it is not surprising that a tidy set of characteristics defining “successful” or “effective” networks has not been empirically identified (Bodin et al, 2017). Below, I briefly assess two trendy models and several methods that have been used for network evaluation.

In the last ten years, two groups of researchers have developed and heavily promoted two models of collective action networking that have been utilized for evaluation: the collective impact model and the PARTNER model. First, Kania and Kramer (2011) wrote about the collective impact model, claiming that successful networks shared five defined characteristics: a common agenda, shared measurement, mutually reinforcing activities, communication, and support organizations. Concerns were raised because Kania and Kramer did not use empirical evidence from a systematic research approach such as grounded theory to create the model, did not root the model in the decades of collective action work that came before their 2011 article, and did not draw from any of the many well-established theories about social connection such as collective action theory (Varda, 2011). Varda and Sprong (2020) offered a competing model, called PARTNER, which stands for Program to Analyze, Record and Track Networks to Enhance Relationships. Varda and Sprong (2020) recommended that network success be measured by the strength of relationships, trust, value, relationship evolution, and achievement of shared goals. Both models lack attention to equity, context, power, and inclusion or exclusion, which have been cited as evidence of their deficiency (Holley, 2012).

Even though these models for network evaluation have been established, most evaluators have not utilized them for network evaluations. Popeier (2018) revealed what evaluators are using for network evaluation, and Bodin et al. (2011) proposed an improvement. First, researchers have used descriptive qualitative, quantitative, and mixed methods to describe network relationships or outcomes (Popeier, 2018). Reflecting the network science rift described above, some evaluators have explored how relationships in a program work, which is reflective of a connectionist point of view (Fredericks & Durland, 2005). Most have studied outcomes derived from networks, which is reflective of a structuralist point of view (Popeier, 2018). However, Bodin et al. (2011) decried the glut of descriptive research and called for empirical investigation and analysis.

Some may interpret the recommendation for empirical study and analysis by Bodin et al. (2011) as a call for the use of inferential statistics, but it is important to reconsider that interpretation. In fact, many quantitative studies have attempted to apply inferential statistics to the study of networks, which is troublesome (Popeier, 2018). Networks are, by their very nature, interdependent. Inferential statistics, which are rooted in linear algebra, are suited for independent observations. The interdependent nature of networks violates the assumption of independence critical to the proper functioning of traditional inferential statistics, especially because the interdependent characteristics of a network are typically the focus of interest (Bodin et al., 2017; Brandes et al., 2013; Fredericks & Durland, 2005; Popeier, 2018). While many evaluators and researchers have used inferential statistics with or without modifications to investigate networks, the results are questionable given the violation of independence of observations (Chung et al., 2008; Hollstein, 2014; Popeier, 2018).

Given this fundamental problem with using inferential statistical methods to study networks, researchers since the 1930s have been developing alternative methods. When Bodin et al. (2011) called for empirical investigation and analysis, they were, in fact, recommending that researchers interested in the effects of relationships use SNA to analyze systematically collected, empirical data using established, formal methods to parse out detailed variation (Bodin et al, 2011; also see Brandes et al, 2013; Fredericks & Durland, 2005; Maroulis & Gomez, 2008). Today, SNA is the most popular quantitative method used by researchers and evaluators to study networks (Borgatti & Halgin, 2011; Popeier, 2018). To explore whether SNA is a sufficient, effective method for evaluating collective action networks, I next describe what SNA is, the history of its development, how it has been used in evaluation, and the strengths and limitations researchers have encountered when using it.

Social Network Analysis

Defining Social Network Analysis

Network scientists debate whether to define SNA merely as a method of data analysis or as social science theory. Originally, SNA was developed as a method of data analysis used within the field of network science, which is based on social network theories. In its basic form, SNA combines graph theory and matrix algebra to analyze the relationships between actors in a system and the nature of the connection between them (Borgatti & Halgin, 2011; Fredericks & Durland, 2005; Groce et al, 2019). The unit of analysis in SNA is the interaction between actors (Fredericks & Durland, 2005). A network researcher is like an architect in reverse; instead of designing the structure, researchers study the intact structure and try to determine how it came to be that way and what difference the building materials and design of that structure have made. “According to this structural paradigm, observed behaviors and social life can be explained by structural relations and the patterns formed by these relations" (Popeier, 2018, p. 326). Based on this idea of patterns in social structure, network researchers can visualize and mathematically quantify relationships and the structures those relationships form (Sandström & Carlsson, 2008).

However, SNA has been elevated by some as a social science theory rather than merely a data analysis method. For example, Borgatti and Halgin (2011) argued that network researchers have contributed to social science theory concepts about structural equivalence, cliques, reciprocity, strong and weak ties, homophily, flow, and more (see also Bodin et al., 2011). Using its mathematical method should not erase its theoretical implications, they said, as math is used to reveal social structure theory. The debate continues about whether SNA is itself theory or method (Fredericks & Durland, 2005), as researchers continue to utilize SNA as both a framework to test theory and as a tool to develop theory (Borgatti & Halgin, 2011). For the purposes of this study, SNA will be used as it was originally intended: as a method of data analysis.

The Development of Social Network Analysis

As a method for data analysis, what has become known as SNA was first developed in the 1930s with hand-drawn graphs. It is now a robust analysis method with multiple software options, online apps, graphing programs, and methodological advances including the creation of types of SNA that can be used for inferential purposes (Fredericks & Durland, 2013). Beginning in the 1930s, sociologists created sociometry, which visualized social relationships. Sociometry was the first approach that became what is now known as SNA (Borgatti et al., 2009; Fredericks & Durland, 2013). Scientists developed matrix algebra and graph theory in the 1940s and 1950s. With the introduction of mathematical approaches, researchers uncovered the phenomenon of cliques and advanced the theory of social structures (Borgatti et al., 2009; Fredericks & Durland, 2013). Through the first few decades of social structure studies in sociology and anthropology, the theory developed that there were deep, abiding patterns of social relationships that could be translated mathematically. In other words, these researchers purported that networks are both sociological and mathematical (Borgatti et al., 2009). By the 1980s, after researchers had developed an approach to visualizing webs of networks using graph theory, network science was an established field in the social sciences with a professional organization, academic journal and conference, and specialized software (Borgatti et al., 2009).

As SNA was incredibly tedious to complete by hand, the development of software starting in the 1970s enabled descriptive analyses, then structural analyses, then greater complexity with roles and subsets (Fredericks & Durland, 2013). These developments spurred the use of SNA by new fields and began pushing SNA out of the bounds of data analysis and into the sphere of social science theory. Physical scientists, management and economics researchers, epidemiologists, those studying public safety and national security, and more began using SNA and contributing to its theoretical and methodological development (Borgatti et al., 2009; Brandes et al., 2013; Fredericks & Durland, 2013; Groce et al., 2019). Development continues, and today researchers can produce statistical models of networks using exponential random graph modeling and can make statistical inference using forms of inferential SNA (Bodin et al., 2017; Chung et al., 2005; Fredericks & Durland, 2013; Sandström & Carlsson, 2008). These new modeling and inferential methods contribute evidence for social science theories, further pushing SNA from its original boundaries as a data analysis tool and into the realm of social science theory. In evaluation, however, SNA has been utilized almost exclusively as a data analysis tool (Popeier, 2018).

Social Network Analysis in Evaluation

As SNA developed and spread into different fields, evaluators took note of the way it was being used by researchers to answer a variety of research questions. SNA especially has received attention within the field of evaluation as evaluators seek ways to understand complexity. Evaluators recognize the influence systems and relationships have on the organizations, policies, programs, and projects that they evaluate (Durland & Fredericks, 2005; Fredericks & Durland, 2005; Patton, 2015; Popeier, 2018). Many have turned to SNA to understand the roles relationships play between elements in a system (Durland & Fredericks, 2005; Fredericks & Durland, 2005; Popeier, 2018). SNA can contribute information assisting with different types of evaluation questions, as will be explored more below, with the essential feature that "the understanding of the phenomenon treats relational connectivity and dependence as central" (Brandes et al., 2013, pp. 11-12; also see Varda & Sprong, 2020). This feature is different from traditional research, in which the units of analysis are individual attributes. SNA can help evaluators to uncover how different relational systems are structured, elements that contributed to the composition of those structures (connectionist perspective), and whether different structures are associated with successful or unsuccessful outcomes (structuralist perspective) (Borgatti et al., 2009; Crona et al., 2011; Popeier, 2018). While the benefits of using SNA are considerable, the main limitation is that evaluators cannot use SNA to establish whether networking produced desired social change outcomes.

Strengths of Social Network Analysis in Evaluation

Evaluators can use SNA to answer different types of evaluation questions, which is a primary benefit of the method. Evaluators can describe network structures at different levels, explore different network roles, and answer questions aligned with the structuralist or connectionist paradigms. Evaluators can focus their evaluation questions on the individuals in a network, subgroups within a network, or entire networks (Fredericks & Durland, 2005; Prell, 2011; Varda & Sprong, 2020). For example, an evaluator focused on the individual level might ask how an individual's relationships were related to their studying behaviors. An evaluator focused on the subgroup level might ask how peer groupings were associated with knowledge attainment. An evaluator focused on the network level might ask how the structure of a network successfully or unsuccessfully produced a flow of information in an educational program. An evaluator also can focus on more than one level to seek similarities and differences since the functioning of these different levels of a network affect one another (Prell, 2011).

These types of questions are common among evaluations that have incorporated SNA (Popeier, 2018). Evaluators also have used SNA to answer questions related to the different roles networks play. Popeier (2018) found evaluations that explored how networks affected the flow of information or goods, the interaction between different elements of the system, social relationships and their ties, or more than one of these. Though the unit of analysis in SNA is relationships rather than individuals' attributes, evaluators have included attribute data as independent or moderating variables, with questions such as how diversity affects network structure and outcomes (Varda & Sprong, 2020).

Most often, evaluators who have used SNA have aligned with the structuralist perspective (whether or not they knew it), with interest in how the structure of networks have been related to the outcomes, achievements, successes, or goal attainment of networks (Bodin et al., 2011; Groce et al., 2019; Guerrero et al., 2013; Popeier, 2018). Evaluators' alignment with structuralism may be because they are focused on the outcomes of the activity of networking without awareness of the differing perspectives within the network sciences about the dimensional aspect of network role. Thus, at the individual level, evaluators strive to connect the network structure to the behavior of individuals as the outcome (Guerrero et al., 2013). At the network level, evaluators study the role of relational ties such as flow of information or resources through the whole network toward an outcome (Bodin & Prell, 2011). However, not everyone agrees with the validity of associating outcomes to network structure (Popeier, 2018; Varda & Sprong, 2020). The practice of linking network structure to external outcomes has been cited as a questionable practice (Popeier, 2018), as has using *process-oriented* data to draw *outcome-oriented* conclusions (Varda & Sprong, 2020). Popeier (2018) concluded, “Few evaluations have succeeded in linking observed network outputs with externally valued network outcomes in a credible manner” (p. 346). This is an important issue for continued consideration and research, especially as evaluators have frequently used SNA in just this way.

Limitations of Social Network Analysis in Evaluation

Though evaluators have found SNA very useful to answer questions about the roles and effects of relationships, they should be aware that the method has discouraging limitations. As software accessibility has increased the popularity of SNA, evaluators who are not well-trained in social network theory or analysis may use the tools improperly (Popeier, 2018). The limitations include that SNA is fundamentally interdependent and descriptive in nature, that it was designed to tune out context, and that it cannot be used as is to correlate outcomes with network characteristics. I will review each of these limitations in turn.

Importantly, SNA produces quantitative *descriptive* data. As mentioned above, pairing SNA with statistical inference methods derived from linear algebra like regression is a questionable practice used surprisingly frequently to link network structure to outcomes (Popeier, 2018). Methods of statistical inference that are based on linear algebra require independence of observations for statistical validity. SNA data is *interdependent*. Entering the numerical output of SNA into, for example, a regression model, violates the assumption of independence and renders results with questionable validity (Bodin et al., 2017; Borgatti & Halgin, 2011; Maroulis & Gomez, 2008; Popeier, 2018). Evaluators may think about addressing the problem of dependence by counting one network or subgroup as a sample of one, leading to very small-*n* SNA studies. Though SNA can handle small to large sample sizes, inferential statistical procedures including multilevel models such as hierarchical linear modeling, which can be used with SNA data, typically require larger sample sizes. Using small-*n* network data with linear inferential statistical or multilevel model procedures results in low statistical conclusion validity that must be addressed (Bodin et al., 2017; Maroulis & Gomez, 2008). Finally, inferential statistics are based on probability theory and should be used with random sampling, which is rarely the case in evaluations involving targeted networks (Carolan, 2014).

Next, using SNA by itself results in quantitative descriptive data and a sociogram or network map that illustrates the structure of the network. Evaluating outcomes requires additional data, including process data and outcome data (Bodin et al., 2017; Groce et al., 2019). Partially because using traditional statistical inference is not advised, establishing a causal link between a network and an outcome has proven elusive (Groce et al., 2019; Popeier, 2018). More recent developments in SNA have enabled statistical modeling of *interdependent* relationships. Exponential random graph models and stochastic actor-oriented models (used with longitudinal data) are two network modeling tools that create random models of networks that can be compared to real networks. The big idea behind these two modeling tools is that if a randomly formed network yields different results from an actual network, then the processes inherent in the actual network must be causing a different effect (Bodin et al., 2017). The procedures are quite complex (Popeier, 2018), and the results help evaluators answer questions about network structure itself, which researchers can then link to outcomes.

Another difficulty in linking network structure to outcomes rests in the chicken-and-egg debate between connectionists and structuralists. When a network is associated with an outcome, connectionists are likely to interpret the result to mean (based on their understanding of theory) that individuals with certain pre-network motivational attributes came together and achieved the outcome. Structuralists, on the other hand, are likely to interpret the result to mean that the structure of the individuals' association with others in the network created the conditions that enabled the outcome. To tease out the causal pathways requires something that SNA alone cannot produce: context. In fact, SNA was designed specifically to ignore context so that the focus of analysis could remain on the relational structure, but this produces what many consider to be unacceptable gaps in understanding (Bodin & Prell, 2011; Bodin et al., 2017; Borgatti & Halgin, 2011; Brandes et al., 2013; Edwards, 2010; Fredericks & Durland, 2005; Maglajlic & Helic, 2012; Maroulis & Gomez, 2008; Marshall & Staeheli, 2015; Popeier, 2018; Sandström & Carlsson, 2008).

Also, though SNA is well-suited for complex, systems-oriented evaluation, the visual and quantitative output is decontextualized. The data is from a single point in time, divorced from the processes that contributed to the structures. Marshall and Staeheli (2015) decried SNA researchers for projecting a "quantitative explanatory certitude" (p. 57) that was theoretically dangerous and methodologically irresponsible. Pairing SNA with other methods, especially qualitative methods, can uncover how a network formed and changed over time (Bodin & Prell, 2011, p. 365; Maroulis & Gomez, 2008); how participants viewed and experienced a network (Sandström & Carlsson, 2008); and the meaning of network relationships and characteristics

(Popeier, 2018). For example, contextual information about the comparative timing of network participation and outcomes could prove critical in establishing temporal precedence, or whether networking came prior to or after certain outcomes were observed. Marshall and Staeheli (2015) cautioned, “The network representations provide order and straight lines to a world of messy relations…We know that as representations of infinitely more complex, subtle, and fluid relations, these network diagrams are but an abstract simplification” (pp. 64-65).

In summary, evaluators can use SNA to make better sense of evaluands that are involved in systems in which relational ties between individuals or groups play a role. Many evaluation questions about individuals, subgroups, and whole networks can be answered, as can questions about the role or purpose of networks. Where SNA has fallen short, however, has been in producing valid results linking network characteristics and activities to outcomes (Popeier, 2018). The necessary and sufficient conditions leading to achievement are unclear. The inferential methods evaluators have used to test statistical hypotheses using SNA data are not widely accepted (Bodin et al., 2017; Borgatti & Halgin, 2011; Maroulis & Gomez, 2008; Popeier, 2018). Most SNA studies have been snapshot studies of single networks. Additional longitudinal studies and network comparison studies could help to fill the gap in understanding the complicated relationship between networks and outcomes (Bodin & Prell, 2011; Groce et al., 2019; Popeier, 2018). Evaluations in which evaluators use context-specific theories to trace network activities and outcomes also could produce more valid results (Popeier, 2018). Pairing SNA with methods that provide context was highlighted by many researchers as an essential approach to understanding SNA results (Bodin & Prell, 2011; Bodin et al., 2017; Borgatti & Halgin, 2011; Brandes et al., 2013; Edwards, 2010; Fredericks & Durland, 2005; Maglajlic & Helic, 2012; Maroulis & Gomez, 2008; Marshall & Staeheli, 2015; Popeier, 2018; Sandström &

Carlsson, 2008). What follows is an exploration of qualitative comparative analysis as a possible method researchers and evaluators could use to address some of the limitations of using SNA.

Qualitative Comparative Analysis

Defining Qualitative Comparative Analysis

Defining qualitative comparative analysis (QCA) requires situating the method within a larger body of comparative methods called configurational comparative research (Ragin, 1998; Thiem, 2017). QCA is used by researchers who are trying to unpack complexity to tease apart multiple, co-occurring causes of outcomes (Ragin, 2005; Roig-Tierno et al., 2017; Sager & Andereggen, 2012). Kahwati and Kane (2019) provided a tidy definition of QCA: A researcher or evaluator "uses set-theory, a branch of mathematics, to identify nonstatistical relationships among explanatory factors and an outcome using qualitative data, quantitative data, or both derived from the cases included in the analysis…and results from a QCA are expressed as solutions" (p. 8). The methodological roots of QCA, which I describe next, rest in comparative case study research, the mathematical theory of sets, the logic of agreement and difference, and Boolean algebra (Ragin, 1987).

Comparative Case Study Research

Cases take center stage in QCA. Using case studies, researchers illuminate real-world behaviors in complex, real-world contexts; they describe and explain naturalistic settings (Yin, 2012). In comparative case study research, researchers compare cases, looking for patterns of similarity and difference (Ragin 1998) using and appreciating both qualitative and quantitative methods (Yin, 2012). Case studies are the most important component of a QCA study; in fact, the quality of a QCA study is judged by whether the analysis provided new interpretation of the cases (Ragin, 1998; 2005). As Ragin (2005) wrote, "The purpose of QCA is to help researchers represent and synthesize what they have learned about their cases" (p. 34). Researchers who use QCA must know their cases intimately, seek comparative data across all cases to avoid flawed results, and return to cases repeatedly throughout the deliberately iterative QCA process (Pattyn, 2019; Schatz & Welle, 2016). Following case study data collection, researchers use QCA procedures to apply set-theory and the logic of agreement and difference to the cross-case analysis data so they can derive the conditions that are associated with outcomes (Befani, 2013; Kahwati & Kane, 2019; Marx et al., 2014; Pattyn, 2019). Ragin (2005) argued that the very basis of case-oriented research is its set-theoretic nature.

Set-Theory, Logic, and Boolean Algebra

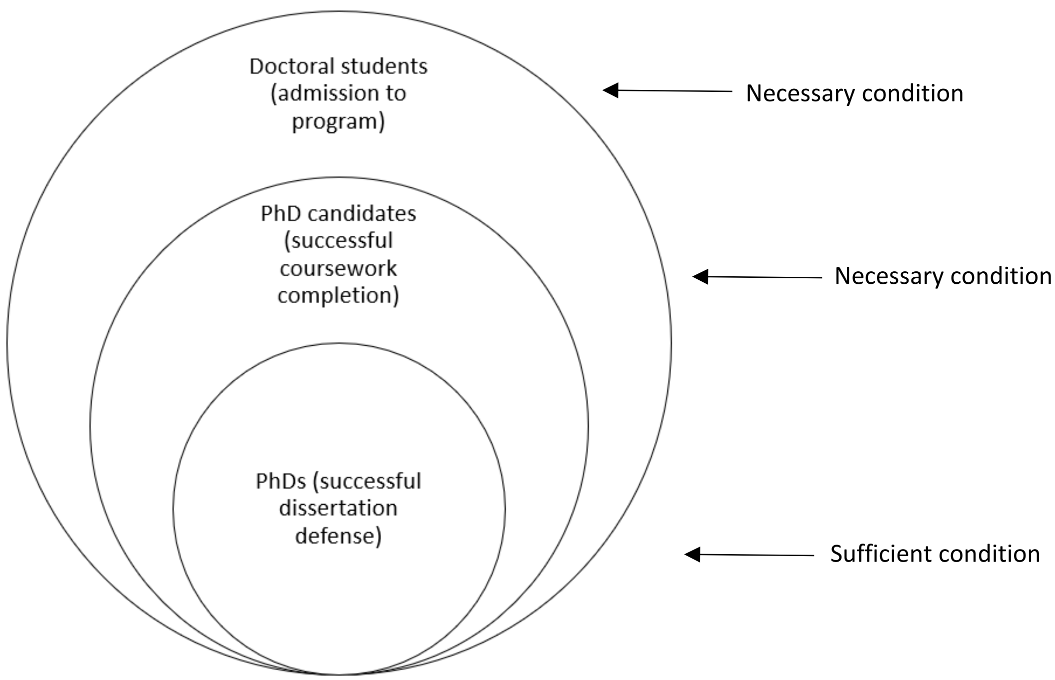
Set theory is a foundational mathematical theory that construes the entire mathematical universe as belonging to sets (Bargia, 2019). Combined with formal logic based on John Stuart Mill's logic of agreement and difference, researchers can deduce which conditions are grouped as sets with specific outcomes (Befani, 2013; Marx et al., 2014; Thiem, 2017). The formal logic, stripped to its most basic idea, is that there are both necessary and sufficient conditions present to belong in a set. If a set is defined as everyone who achieved a certain outcome, researchers can use QCA to elicit what conditions were necessary and/or sufficient for someone to belong to the outcome set. The pattern of these necessary and sufficient conditions is known as a "complex causal relationship" (Befani, 2013; Hollstein & Wagemann, 2014; Kahwati & Kane, 2019; Mello, 2020).

The purpose of QCA is to link causal conditions to outcomes (Marx et al., 2014). The method enables researchers to explore causal complexity, which incorporates the concepts of equifinality, conjunctural causation, and asymmetrical causation (Kahwati & Kane, 2019; Marx et al., 2014). Equifinality means that are multiple ways to achieve an outcome; conjunctural causation means that a condition may not lead to an outcome on its own but may lead to an outcome in combination with other conditions; and asymmetrical causation means that although a condition leads to an outcome, it does not mean that absence of that condition will prevent the outcome (Befani et al., 2007; Hollstein & Wagemann, 2014; Kahwati & Kane, 2019; Marx et al., 2014; Mello, in press; Ragin, 1998; Sager & Andereggen, 2012). The analysis of causal complexity results in a solution of necessary and sufficient conditions, where necessary conditions are those that must be present for the outcome to occur and where sufficient conditions are those that, singularly, are conjoined with the outcome.

See Figure 2, which illustrates a simple example of sets with necessary and sufficient conditions for a doctoral degree. At a traditional brick-and-mortar university, everyone who achieved a doctoral degree had been admitted to one of the doctoral programs at the university. Admissions to a doctoral program at the university was a *necessary* condition to the outcome of doctoral degree. However, admissions did not always result in a doctoral degree, so the condition of admission was not *sufficient* to the outcome of doctoral degree. With a sufficient condition, the outcome will always be present. At the same university, successful completion of coursework in the doctoral program earned people membership into a subset of PhD candidates. But not all PhD candidates earned doctoral degrees, so successful completion of coursework was a *necessary but insufficient* condition for membership in the subset of PhDs. Finally, all who successfully defended dissertations earned doctoral degrees, and everyone who did not earn a doctoral degree did not successfully defend. The condition of successful defense was always present for those who earned doctoral degrees. Therefore, successful defense was a *sufficient* condition to membership in the set of PhDs from that university. The result of this logic exercise is a string of necessary and sufficient conditions that link to an outcome. In this case, the outcome was a doctoral degree.

Figure 2

Set with Subsets Showing Necessary and Sufficient Conditions for Membership



The doctoral program example above explored the case of one university. To systematically analyze the conditions present and not present across *multiple* cases, QCA employs Boolean algebra, "the algebra of logic" (Ragin, 1987, p. 85). The result, or solution, is the combination of conditions that, across cases, were necessary and/or sufficient for the outcome to occur. This string of necessary and sufficient conditions is called a causal pathway, which is not to be confused with causal inference (Kahwati & Kane, 2019; Ragin, 1998; 2005). Although some mixed messaging exists about causality and QCA, which I explore below, the developer of QCA himself said that QCA was not created to establish causal inference but "to make sense of cross-case patterns and thereby aid the causal interpretation of cases, using theory and accumulated substantive knowledge as guides" (Ragin, 2005, pp. 33-34). To understand this better requires a brief review of why QCA was developed.

The Development of Qualitative Comparative Analysis

QCA was developed in the late 1980s by Charles C. Ragin, a political sociologist (Ragin, 1987). Ragin was a traditional quantitative methodologist by training and practice, specializing in interaction effects in regression. He was unsatisfied when applying those methods in several social science contexts (Marx et al., 2014). He grew increasingly frustrated by inferential statistics when he wanted to analyze multiple causal conditions leading to complex outcomes (Marx et al., 2014). In his search for solutions, he initially developed QCA to bring together the strengths of qualitative, case-oriented research approaches with quantitative, variable-oriented research approaches in a way that would enable the analysis of causal complexity (Befani et al., 2007; Cragun et al., 2016; Kahwati & Kane, 2019; Marx et al., 2014; Ragin, 1998; Sager & Andereggen, 2012). At the heart of this idea was this sentiment by Ragin (2005): "For many, if not most, case-oriented researchers, the idea that a single causal condition can have a net, independent effect across cases makes little sense" (pp. 34-35).

In his original iteration of QCA, Ragin relied on Boolean algebra, which required dichotomous data (Ragin, 1987). Since then, he and other researchers have developed tools and methods to expand QCA, and researchers now can analyze nominal, ordinal, interval, or ratio data (Marx et al., 2014). Goodness-of-fit tests have been developed, as have different versions of QCA to incorporate a temporal dimension (Kahwati & Kane, 2019). Software packages, including a QCA package for R, have been developed, which has led to a greater number of researchers from a wide variety of fields using QCA (Roig-Tierno et al., 2017). From a bibliometric review, 425 of 469 articles including QCA were published after the year 2000

(Roig-Tierno et al., 2017). Social science researchers, especially in Europe, have embraced QCA in fields including business and management, political science, sociology, environmental studies and sciences, public health, international relations, and more (Mello, 2020; Roig-Tierno et al., 2017). A website (www.compasss.org) is devoted to cross-case analysis, and researchers can attend conferences and workshops that heavily feature QCA. As QCA research expanded across fields of study and became more prevalent, evaluators grew curious about whether it could be applied usefully within the field of evaluation.

Qualitative Comparative Analysis in Evaluation

QCA is a relatively new method to evaluators, so it has not yet been used to evaluate networks. Analyses of published QCA articles have found about 20 relating to both QCA and evaluation (Gerrits & Verweij, 2016; Roig-Tierno et al., 2017), despite rapid growth in the number of articles in the social sciences starting in the late 2000s (Mello, 2020). In one analysis, only seven of nineteen evaluation articles discovered were about studies for which evaluators used QCA; the others described QCA or mentioned the method as part of a broader topic (Gerrits & Verweij, 2016). Evaluators that have taken the leap have found that QCA can help them uncover conditions present with desired outcomes (Cragun, et al., 2016; Kien et al., 2018; Schatz & Welle, 2016; Warren et al., 2013), and QCA was recommended as an alternative to quantitative impact evaluation in appropriate international development contexts (Stern et al., 2012). The usefulness of QCA to evaluators is next explored through the lenses of its strengths and limitations.

Strengths of Qualitive Comparative Analysis in Evaluation

Evaluators' use of QCA reflects what it was designed to do well, which includes unpacking causal complexity, being useful in different types of contexts including small-*n* to large-*n* contexts, and offering an alternative when contexts do not adhere to inferential statistical assumptions. Questions evaluators can answer with QCA are about uncovering set-relations, those combinations of necessary and sufficient conditions that are related to outcomes (Hollstein & Wagemann, 2014; Schneider & Wagemann, 2010). QCA evaluation questions, in other words, target an increase in understanding the elements that are linked with something working or not working. It is better suited for learning than for accountability (Pattyn et al., 2019). In other words, as opposed to a goal of establishing causal attribution (desired for accountability), evaluators with a goal of program improvement and learning can use QCA to understand the conditions programs should replicate because those conditions typically are present with desired outcomes. QCA offers a more systematic approach than do other qualitative methods that relate conditions to outcomes, including contribution analysis, logic models, and necessary condition analysis (Thiem, 2017). The primary benefits to using QCA are its flexibility and its ability to handle causal complexity, each of which I explore next.

First, evaluators will find a great deal of flexibility in the type of data they can use with QCA. It is inherently a mixed methods approach that brings together strengths of qualitative, case-oriented methods and quantitative, variable-oriented methods (Befani et al., 2007; Cragun et al., 2016; Hollstein, 2014; Hollstein & Wagemann, 2014; Kahwati & Kane, 2019; Marx et al., 2014; Mello, in press; Ragin, 1998; Roig-Tierno et al., 2017; Sager & Andereggen, 2012). Case-oriented researchers typically want to learn from a relatively small number of cases that are applicable to the research questions. Variable-oriented researchers typically want to infer relationships between variables in order to generalize to a population. Comparing cases allows for the exploration of complexity, and QCA offers a systematic way to compare complex cases across several variables to discover whether conditions are necessary or sufficient to an outcome (Hollstein & Wagemann, 2014; Marx et al., 2014; Ragin, 1998).

Also, using QCA, evaluators do not have to meet inferential statistical assumptions (Downey & Stanyer, 2014; Kahwati & Kane, 2019). Rather, the assumptions of QCA are that the purpose of the study is *not causal inference but causal interpretation,* meaning that researchers or evaluators will use their extensive case knowledge and grounding theory to inform their understanding of the patterns that emerge. This grounding in knowledge, theory, and causal complexity will inform their interpretation of conditions involved in outcomes (Ragin, 2005). Because evaluators are freed from the assumptions required by inferential statistics, they do not need to worry about sample sizes. QCA has been used for small-*n* case comparisons up to very large-*n* case comparisons, though it typically is used for small- to medium-*n* samples (Downey & Stanyer, 2014; Hollstein & Wagemann, 2014; Kahwati & Kane, 2019). Most QCA researchers use between ten and ninety cases (Marx et al., 2014). Researchers have used samples of individuals, institutions, and even countries, so QCA offers great flexibility with the target population for samples as well (Cragun et al., 2016). In addition to using QCA for its applied purpose of tracking conditions to outcomes, evaluators and researchers can use QCA to analyze similarities and differences between cases, test existing theories, test new ideas in order to develop theories, and extend or refine theories (Befani, 2013; Cragun et al., 2016; Marx et al., 2014; Pattyn, 2019; Schneider & Wagemann, 2010; Stern et al., 2012).

Importantly, Ragin (2005) named causal complexity one of the assumptions of QCA. As described above, causal complexity recognizes that different outcomes may arise based on context. QCA is especially appealing to evaluators who align with realist evaluation, a type of evaluation through which evaluators seek to address causal complexity (Befani, 2013; Sager & Andereggen, 2012). “The main value-added of QCA [for evaluators] is its achievement of the goals of realist synthesis in a systematic and comparative manner by providing context-sensitive conjunctural explanations for outcomes, while preserving the substance and the explanatory richness of the cases” (Sager & Andereggen, 2012, p. 72). Evaluators who assume that different outcomes may occur based on contextual factors will agree with this basic philosophy of QCA. For contextually complex evaluands, the results of QCA can answer some evaluation questions better than variable-oriented research that produces mono-causal results (Befani et al., 2007; Gerrits & Verweij, 2016; Pattyn et al., 2019; Ragin, 1998; Roig-Tierno et al., 2017; Sager & Andereggen, 2012; Stern et al., 2012). QCA “represents a shift from focusing causal analysis on variables taken out of their specific context. Locating variables in the context of the ‘case’ and conducting within-case analysis alongside comparisons across cases has opened up major new opportunities for causal analysis that are still largely ignored in evaluation practice” (Stern et al., p. 27). However, the purpose of QCA is not to replace variable-oriented approaches (Ragin, 2005). More about QCA and the causality debate is discussed below as a limitation.

Limitations of Qualitive Comparative Analysis in Evaluation

QCA has been viewed with suspicion by strictly qualitative researchers and by strictly quantitative researchers. Qualitative researchers doubt the qualitative integrity of a method that quantizes qualitative data and that uses algebra and a computer program to analyze case study data (Cragun et al., 2016). Quantitative researchers doubt the integrity of a method that relies so heavily on a researcher’s qualitative and subjective case knowledge to arrive at anything related to causality (Cragun et al., 2016). Next, I review the limitations of QCA that evaluators face, including the causality debate, limits to generalization, analytical considerations, and intensity required.

First, according to set-theory and formal logic, QCA surfaces causal pathways, which are the conditions that lead to an outcome (Befani et al., 2007; Kahwati & Kane, 2019; Marx et al., 2014; Ragin, 1998; 2005; Sager & Andereggen, 2012). In the ongoing debates about QCA, this assertion has been a primary target for researchers who question the soundness of the method. These critics have used the failure of simulated data to produce the same results as real data as a primary indicator of the invalidity of QCA (De Meur et al., 2012; Marx et al., 2014). However, QCA supporters have countered that simulated data is inappropriate for QCA, just as it is not reasonable to use simulated data to test the veracity of case studies (De Meur et al., 2012; Marx et al., 2014). Cases are the heart of QCA, and researchers must be intimately knowledgeable about them (Mello, 2020; Ragin, 2005). QCA researchers return to cases repeatedly to update their analyses (Ragin, 2005; Schneider & Wagemann, 2010). Traditional quantitative researchers interpret this as a type of subjective fishing for results, while qualitative researchers consider this a necessary and effective analysis practice (Patton, 2015). QCA researchers understand updating analyses as responsible treatment of configurational comparative data (De Meur et al., 2012; Marx et al., 2014). “It should be pointed out that this does not have anything to do with data manipulation,” Hollstein and Wagemann (2014) wrote. “Quite the contrary, it is a process of acknowledging evidence and using this evidence to reformulate the previous hypotheses, which could be referred to as ‘learning’ in the most positive sense” (p. 249).

Critics also have complained that QCA has been touted as a replacement for regression analyses, although the developer of QCA has strongly refuted that (Ragin, 2005). The purpose of QCA, he said, is *not* to replace variable-oriented research and its methods to determine causal inference (Ragin, 2005). He also reiterated that QCA produces causal interpretation, not causal inference, where causal interpretation is the result of case knowledge and theory applied to causally complex QCA results and where causal inference is the statistical result of experimental hypothesis testing (Ragin, 2005). Mixed messages abound, however, when QCA researchers use the term "causal inference" to describe the product of QCA (Befani, 2013; Thiem, 2017). In fact, Thiem (2017) wrote in an article published by an evaluation journal, "It is undisputed that the purpose of QCA is causal inference" (p. 421). Ragin has written repeatedly that inference is, in fact, *not* the purpose (Marx et al., 2014; Ragin, 1998; 2005).

At the crux of the debate is the old paradigmatic battle between quantitative researchers and qualitative researchers. Ragin sought to bridge the two methodologies with QCA, but QCA has been judged based on both constructivist values and post-positivist values (De Meur et al., 2012; Ragin, 2005). In response to critics who reject QCA based on the standards of post-positivist, variables-oriented research—specifically regression analysis—Ragin (2005) wrote, "QCA is based on the algebra of sets, not on linear algebra, the basis of regression analysis. QCA's analytic engine is fueled by set-theoretic relations, not correlation…Set-theoretic relations concern explicit connections, while correlations are symmetrical; set-theoretic relations are well-suited for questions about necessity and sufficiency, while correlations are not" (p. 37). To stay out of the paradigmatic brawl, Kahwati and Kane (2020) recommended that, at a minimum, researchers and evaluators avoid the term "causal inference" when referring to QCA, especially because it can "be a flashpoint for peer reviewers" (p. 12).

Another debate concerns whether researchers can generalize the findings from QCA. Some researchers confidently state that one should not generalize findings from QCA, especially given the philosophy of causal complexity (Befani et al., 2007; Kahwati & Kane, 2019; Roig-

Tierno et al., 2017; Sager & Andereggen, 2012). Yin (2012) addressed the question of generalization in case study research, differentiating between statistical generalization and analytic generalization. He wrote, “Analytic generalizations depend on using a study’s theoretical framework to establish a logic that might be applicable to other situations” (p. 18). Some QCA researchers mirrored the idea that results that uncover patterns of what does and does not work across cases might be applicable to other, similar cases (Befani, 2013; Gerrits & Verweij, 2016; Pattyn et al., 2019; Schneider & Wagemann, 2010; Stern et al., 2012). Evaluators should very carefully consider the limits of generalization when they use QCA.

Evaluators also should be aware of the limitations produced by several analytical complexities when they use QCA. Primarily, the method is sensitive to cases and the number of conditions. Sensitivity to cases means that the inclusion or exclusion of specific cases can change the results because the method incorporates context (Kahwati & Kane, 2019; Marx et al., 2014; Sager & Andereggen, 2012). Because the process is so bound to the evaluator’s case knowledge, bias is a threat to validity (Sager & Andereggen, 2012). The evaluator must understand the cases very well; deliberately determine, based on theory and the evaluation questions, which cases to include and exclude; and execute the analysis process with fidelity and transparency so that a future researcher with the same case data in hand could replicate the analysis (Sager & Andereggen, 2012).

Another limitation is that QCA is sensitive to the number of conditions because of the use of Boolean algebra, which necessitates that only a handful of conditions be included in an analysis (Marx et al., 2014; Schneider & Wagemann, 2010). Using many conditions results in many possible combinations of conditions, which become uninterpretable (Kahwati & Kane, 2019; Marx et al., 2014; Pattyn et al., 2019; Schneider & Wagemann, 2010). This constraint is not unique to QCA, but researchers must consider this when deciding whether to use QCA.

As may be clear from the preceding discussion about strengths and limitations, QCA is an involved method. Researchers begin with gathering case information until they are intimately knowledgeable about the cases, and they continue to build upon and utilize that knowledge throughout the analysis process (Marx et al., 2014; Pattyn, 2019; Ragin, 2005; Schatz & Welle, 2016). Meanwhile, they also are knowledgeable about the social science theory they are using, and they continue to build upon and utilize that knowledge to make decisions throughout the analysis process (Befani et al., 2007; Ragin, 2005; Sager & Andereggen, 2012). Gaps in data create problems by limiting the potential for comparing across cases (Pattyn et al., 2019). For the analysis to provide what is needed for evaluation, cases must include those that achieved the outcome and those that did not achieve the outcome so that conditions leading to the outcome can be discovered (Schatz & Welle, 2016). Finally, each outcome the evaluator wishes to explore requires unique analysis, as the process only manages one outcome at a time. That means for each outcome, the evaluator must select the appropriate cases and conditions and iteratively conduct the analysis (Pattyn et al., 2019).

Despite these limitations, evaluators have been encouraged to use QCA as an approach that can provide causal interpretation with smaller sample sizes and within highly complex conditions. If the approach is done with fidelity and transparency, evaluators can yield results that unearth conditions that are necessary and sufficient to the outcome of interest (Gerrits & Verweij, 2016; Pattyn et al., 2019; Sager & Andereggen, 2012; Schatz & Welle, 2016; Stern et al., 2012; Thiem, 2017). QCA was developed to systematically analyze comparative case studies, and “the basic motivation behind a QCA should always be to learn more about cases” (Schneider & Wagemann, 2010, p. 400). The method works best for that purpose.

QCA was introduced in this chapter as a possible method to pair with SNA. Now that the individual examination of SNA and QCA is complete, what follows is an examination of whether the two methods are complementary.

Bringing Two Methods Together

The main question of this study is whether QCA can be paired effectively with SNA to contribute to an understanding of networking outcomes. The purpose, values, and underlying mechanisms of both SNA and QCA indicate that the methods will be compatible. A brief review of prior research that paired social networking and case study methods provides further evidence. Here, I briefly describe those prior studies and discuss how they indicate high methodological compatibility.

Three prior studies were found that paired comparative case studies with SNA, only one of which paired SNA with QCA (Bodin et al., 2017; Sandström & Carlsson, 2008; Velastegui, 2013). None of the studies paired SNA with QCA to answer a question about the non-relational outcomes of networking, so that methodological question remains unanswered.

- Bodin et al. (2017) used a mixed-methods approach with exponential random graph modeling and comparative case studies to explore collaboration in ecosystem-based management. Exponential random graph modeling (EGRM) enables inferential testing of whether an actual network has characteristics different from a randomized network model. The researchers’ methodological contribution was combining EGRM with case study data to answer a question about whether different network characteristics were associated with a different outcome.

- Sandström & Carlsson (2008) studied a policy network using an explanatory mixed methods case study. They began with SNA, which they confirmed using comparative case study data. The researchers' methodological contribution was the use of qualitative case study data to confirm descriptive SNA data.
- For a dissertation study, Velastegui (2013) used SNA to uncover individuals' structural positions in a network and then successfully used QCA to identify pathways to becoming leaders and influencers. The researcher's methodological contribution was pairing SNA and QCA to study relationship structures.

For evaluators interested in the question of whether networking was associated with an outcome, the approaches these researchers used fell short. The purpose of using QCA is to unearth those causal pathways for interpretation. To that end, QCA has been used with network studies that relied on qualitative network data, including interviews and ethnographic data (Hollstein & Wagemann, 2014; Coburn et al., 2012). In these studies, the authors successfully contextualized social network data with a qualitative approach, and QCA enabled the authors to link the network data to the outcome of interest.

The use of comparative case studies and SNA in the examples above indicates that case-based methods and SNA are compatible. Neither SNA nor QCA is limited by sample sizes or statistical assumptions, so the methods can be used together without those strictures. Both approaches were designed to work within the complexity of systems, seek relational connections, and value qualitative and quantitative data. SNA and QCA can be used in situations of complexity, which almost always describes systems (Hummelbrunner, 2011). Both SNA and QCA unpack relationships. SNA does so for relationships between actors, and QCA does so for relationships between conditions that arise from cases. Set theory, upon which QCA is based, is essentially about relationships between sets. Networks consist "of a set of relations that apply to a set of social actors, as well as any additional information on those actors and relations" (Prell, 2011, p. 31). A network essentially is a system that is well-suited for set-theory treatment. Finally, both SNA and QCA are perfect for researchers who recognize the value of quantitative and qualitative methodologies and approaches, and both SNA and QCA have been identified as essentially mixed methods (Hollstein & Wagemann, 2014; Popeier, 2018). All of these factors suggest that QCA will work well to fill the gaps left by SNA to answer the question of whether networking produces outcomes.

Rationale for the Current Study

Rooted in the prior research and unanswered questions, the purpose of this study is to discover whether combining SNA with QCA produces more informative results, when compared with SNA alone, about how collective action networking contributes to desired social change outcomes. For the purposes of this study, the *contribution* I study refers to its meaning within the field of evaluation. For evaluators, contribution is a determination of whether certain activities *helped to* cause the observed outcomes, as opposed to attribution, which implies that activities were shown to cause the outcomes (Almquist, 2011).

I will use a scaffolded series of three studies to explore the contribution QCA can make to the evaluation of networks. First, I will use a nonexperimental, descriptive, quantitative approach including SNA to study the structures and relationship characteristics of a network. Second, I will use an explanatory mixed methods case study (similar to Sandström & Carlsson, 2008) to study the intended and unintended outcomes from networking experiences. For this mixed methods study, I will use the descriptive quantitative SNA study for the quantitative strand. Based on the results from the quantitative strand, I will develop an interview protocol and select participants for semi-structured interviews, in addition to reviewing archival documents about a network. I will conclude the explanatory mixed methods case study by using QCA to integrate the quantitative (including SNA) and qualitative data. For the third study, I will compare the results gleaned from Study 1 using SNA to the results gleaned from Study 2 using QCA with SNA. This comparison will indicate whether additional information about networking outcomes can be produced using QCA with SNA versus using SNA alone.

The research questions guiding the study are as follows:

Study 1: Social Network Analysis

- To what degree are various network structures and relationship characteristics present for the E Alu Pū network and member groups?
- To what degree have intended outcomes been achieved by the E Alu Pū network and member groups?

Study 2: Qualitative Comparative Analysis

- For the E Alu Pū network, what intended and unintended outcomes emerge from networking experiences and activities?
- For the E Alu Pū network, what conditions are necessary and sufficient to achieve the intended outcomes?
- How does qualitative data about the E Alu Pū network help to explain or contextualize quantitative survey data about network relationships, structures, and outcomes?

Study 3: Comparison of Findings from Study 1 with Findings from Study 2

- When compared with using SNA alone, what additional understanding about networking outcomes can be gained by using QCA with SNA?

Answering these questions will contribute to the knowledge base for five audiences: (1) the E Alu Pū network and its stakeholders will benefit from learning about the products of a networking strategy and experiences of the network member groups. (2) Evaluators, both practitioners and researchers, will benefit from a clear method for integrating SNA and QCA to evaluate network outcomes. (3) Network facilitators and funders will benefit from improved information about networking that can affirm whether the investment in networks is supported by the evidence. (4) Network scientists will benefit from a method that can provide a new layer of information to build upon the current understanding of the different dimensions of networks and aid in the interpretation of SNA data. (5) Mixed methods researchers will benefit from new information about whether QCA can be an effective and advisable mixed methods integration approach. Because this study combines two methods in a new way for a new purpose, it has the potential to contribute to the knowledge base of these multiple audiences.

Chapter Two Summary

SNA and QCA both arose from a need to analyze data that is steeped in complexity and related to other data. Researchers began developing what is now SNA in the 1930s, while QCA was developed in the late 1980s. Although SNA has had 50 more years of development, researchers have not created methods to adjust SNA for contextualization. Newer developments in SNA like exponential random graph models and stochastic actor models are expanding how researchers can use SNA by enabling inferential treatment of interrelated data. Still, the types of questions researchers can answer with those models are limited. In response, most researchers and evaluators using SNA have addressed its limitations by pairing SNA with other methods. Using SNA as part of a mixed methods approach is typical. In past studies that have combined SNA with comparative case approaches, authors have been able to address the structure of relationships and their importance (Bodin et al., 2017; Coburn et al., 2012; Sandström & Carlsson, 2008). What has not been explored is what QCA can contribute to quantitative SNA via systematic comparative case analysis that results in necessary and sufficient conditions to outcomes. SNA and QCA have been suggested by other researchers as a pairing worth exploring (Marx et al., 2014; Serdült & Hirschi, 2004). They are theoretically complementary. Based on the discussion throughout this paper, they appear methodologically aligned. What is lacking is an empirical example of using the two methods together for network evaluation. Therefore, the key question remains unanswered: When compared with using SNA alone, what additional understanding about networking outcomes can be gained by using QCA with SNA?

CHAPTER THREE: METHODOLOGY

Social network analysis (SNA) is a preferred method to evaluate collective action networks, a type of network defined by people coming together for a shared social change purpose (Ernstson, 2011). However, using SNA reveals a small, focused window into the network. Networks are complex and operate as systems, and some researchers have lamented that by using SNA, they excluded important contextual information (Borgatti & Halgin, 2011; Brandes et al., 2013; Maglajlic & Helic, 2012). Other researchers have warned that using traditional inferential statistics with SNA data violates the assumption of independence of observations (Bodin et al., 2017; Brandes et al., 2013; Chung et al., 2008; Fredericks & Durland, 2005; Hollstein, 2014; Popeier, 2018). Evaluators have been left with limited and often unsatisfying options to understand whether networking is linked with intended social change outcomes. One of the options evaluators have used is mixed methods, producing a more well-rounded understanding of networks by incorporating contextual information. Still, for program directors and funders who want evaluators to be able to help programs identify what program elements are associated with outcomes, adding contextual information may not go far enough. A method called qualitative comparative analysis (QCA) may help to fill this gap, as it was designed for causal interpretation of conditions and outcomes in complex situations in which context is relevant.

To address the need for evaluative information to assess the outcomes of collective action networking, I will compare results from the evaluation of a case network using SNA to results from the evaluation of the same case network using QCA with SNA. This chapter describes the methods and methodologies I will use to execute the study. Beginning with the research purpose, questions, and design overview, I then explain the three interwoven studies that comprise this research: (1) a quantitative study of a network using SNA, (2) an explanatory mixed methods case study using the SNA data with QCA, and (3) a comparative study of the results from the first two studies.

Research Purpose and Questions

The purpose of this study is to discover whether combining SNA with QCA produces more informative results, when compared with SNA alone, about how collective action networking contributes to desired social change outcomes. I am using the word “contribute” here as it is used within the field of evaluation: as a determination of whether specific activities influenced or played a role in the observed outcomes (Almquist, 2011). To achieve the study purpose, I will use a series of three scaffolded studies focused on the E Alu Pū network (Hawaiian that translates roughly to “move forward together”). The network is comprised of 36 community-based resource management groups based throughout the Hawaiian Islands.

In **Study 1,** I will gather archival survey data and analyze it using descriptive statistics and SNA to examine the relationships, structures, and outcomes in the network and member groups. In **Study 2,** I will use an explanatory mixed methods case study design. For the quantitative strand, I will use the same survey data from the case network in Study 1 to examine relationship structures and patterns in addition to and outcomes. Then based on those quantitative results, I will gather qualitative data using interviews and organizational documents to explore intended and unintended outcomes for the case network and member groups. The reason for using both forms of data to support the case is to develop an in-depth understanding of the network and its member groups. I will integrate the quantitative and qualitative results using QCA to discover any conditions that are necessary and sufficient to the network’s intended outcomes. Finally, in **Study 3,** I will compare the results from Study 1 with the results from

Study 2 to explore what QCA can contribute to an understanding of collective action network outcomes. The research questions guiding this study are as follows:

Study 1: Social Network Analysis

- To what degree are various network structures and relationship characteristics present for the E Alu Pū network and member groups?
- To what degree have intended outcomes been achieved by the E Alu Pū network and member groups?

Study 2: Qualitative Comparative Analysis

- For the E Alu Pū network, what intended and unintended outcomes emerge from networking experiences and activities?
- For the E Alu Pū network, what conditions are necessary and sufficient to achieve the intended outcomes?
- How does qualitative data about the E Alu Pū network help to explain or contextualize quantitative survey data about network relationships, structures, and outcomes?

Study 3: Comparison of Findings from Study 1 with Findings from Study 2

- When compared with using SNA alone, what additional understanding about networking outcomes can be gained by using QCA with SNA?

In Table 1 below, I provide a summary of the study, linking the research questions to the various components of the study. (I also have included the table in Appendix A.) Then, through the remainder of this chapter, I describe the research design choices I have made to answer these research questions, including details about how I will handle each of the three studies.

Table 1

Research Matrix Summarizing the Study

Research questions	Indicators	Data sources	Data collection methods	Data analysis methods
To what degree are various network structures and relationship characteristics present for the E Alu Pū network and member groups?	Relationship and structure measures	KUA	Archival survey data	Social network analysis
To what degree have intended outcomes been achieved by E Alu Pū member groups?	Outcome variables	KUA	Archival survey data	Frequency counts, descriptive statistics
For the E Alu Pū network, what intended and unintended outcomes emerge from networking experiences and activities?	Comments linking networking and outcomes	E Alu Pū, KUA	Interviews, documents, archives	Constant comparative analysis
For the E Alu Pū network, what conditions are necessary and sufficient to achieve the intended outcomes?	Relationship and structure measures, outcome variables, comments linking networking and outcomes	E Alu Pū, KUA	Archival survey data, interviews, documents, archives	Qualitative comparative analysis
How does qualitative data about the E Alu Pū network help to explain or contextualize quantitative survey data about network relationships, structures, and outcomes?	Relationship and structure measures, outcome variables, comments linking networking and outcomes	Qualitative results, quantitative results	Archival survey data, interviews, documents, archives	Integration of QUAN and QUAL results
When compared with using SNA alone, what additional understanding about networking outcomes can be gained by using QCA with SNA?	Results from Study 1 and Study 2	SNA results, QCA results	SNA, QCA	Comparison of SNA results and QCA results

Research Design Overview

For this research, I will compare two studies to ultimately draw a conclusion about the value of integrating QCA with SNA for network evaluation. The studies build upon each other and overlap, as illustrated in Figure 3 below. Overall, I will use mixed methods for this research. I will use a nonexperimental descriptive design for the first study, an explanatory mixed methods case study for the second study, and then will compare the results from those two studies. Below, I discuss the purpose of and justification for these decisions.

First, for this research, I will use mixed methods, a research method "in which the investigator collects and analyzes data, integrates the findings, and draws inferences using both qualitative and quantitative approaches or methods in a single study or a program of inquiry" (Tashakkori & Creswell, 2007, p. 4, as reported in Creswell & Plano Clark, 2018, p. 4). Mixing methods is more than simply combining qualitative and quantitative data. Instead, using a mixed methods design is related to a world view or paradigm that honors "multiple ways of seeking and hearing, multiple ways of making sense of the social world" (Greene, 2007, p. 20, as reported in Creswell & Plano Clark, 2018). Given my goal for this study to improve methods in the service of social change, the paradigmatic flexibility of mixed methods aligns well.

Second, I will use a quantitative, nonexperimental, descriptive approach for the first study. Gliner, Morgan, and Leech (2017) described nonexperimental approaches as those than do not use active intervention or manipulation by researchers. In addition, descriptive designs do not use independent variables, compare outcomes between groups, or determine strength of relationship between variables (Gliner et al., 2017). Because I am not hoping to infer results to a broader population, predict trends, compare groups, or correlate variables, a descriptive, nonexperimental design suffices.

Third, I will use an explanatory mixed methods case study for the second study. I discussed the reasons for using mixed methods above, so here I briefly will explain why I am using a case study, specifically a mixed methods case study, and more specifically an explanatory mixed methods case study. A case study, according to Yin (2014), "investigates a contemporary phenomenon (the 'case') in depth and within its real-world context," which is often complex with "many more variables of interest than data points" so that it "relies on multiple sources of evidence" (pp. 16-17). Case studies work well with research questions that ask "how" and "why" about phenomena over which the researcher does not have control (Yin, 2018). All of these case study characteristics are true for this research. Some researchers have been critical of SNA because it does not incorporate contextual factors (Borgatti & Halgin, 2011; Brandes et al., 2013; Maglajlic & Helic, 2012). Using a case study with SNA will help to create a more well-rounded understanding of the phenomenon of collective action networking than using a singular qualitative or quantitative design (Creswell & Plano Clark, 2018; Gerring, 2017; Yin, 2014). Importantly for this research, case studies provide the rich, varied data about outcomes and conditions that are needed for QCA.

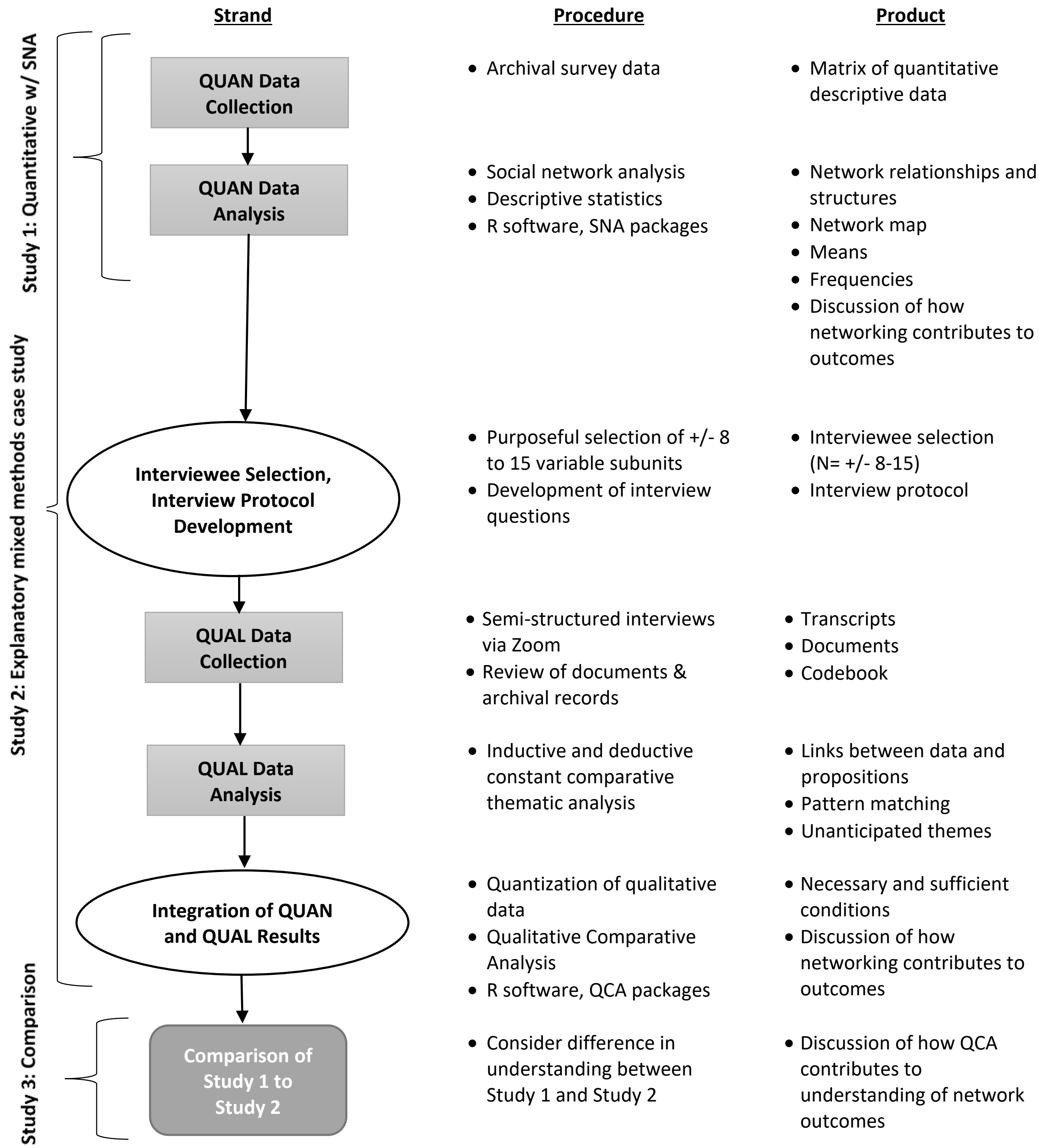
Further, the purpose of a mixed methods case study is to develop an in-depth description and understanding of a case and its complex, multifaceted characteristics using both quantitative and qualitative data (Creswell & Plano Clark, 2018). The quantitative and qualitative strands each provide unique information necessary to fully understand the case. Plus, QCA is inherently a mixed methods case study integration approach, as one uses QCA to integrate quantitative and qualitative data from multiple cases to derive necessary and sufficient conditions toward an identified outcome.

Finally, the concept of an *explanatory* mixed methods research design centers around the timing and role of the quantitative and qualitative strands. In explanatory mixed methods studies, the quantitative strand occurs first. Based on the quantitative findings, a qualitative strand is designed to elucidate the quantitative results (Creswell & Plano Clark, 2018). To begin to understand the case network, I need to understand the network structures and characteristics. I will rely on qualitative data, though, to contextualize and explain the network and the outcomes. To integrate the two strands, I will quantize the qualitative data and analyze the results together using the algorithmic functions of QCA.

To summarize the research design, the study began with the selection of the case and, for QCA, identification of the outcomes and conditions upon which I will focus. Researchers using QCA may change or revise the conditions being studied during the analytic process, but identifying the conditions before beginning the study enables researchers to collect the appropriate data (Mello, 2020). The remaining procedures for the three scaffolded studies are illustrated in Figure 3. In the first study, I will use a quantitative, nonexperimental, descriptive approach. I will analyze the E Alu Pū network using archival survey data that asked member groups about their connections and outcomes. This study will result in conclusions about network relationships, structures, and outcomes. In the second study, I will use an explanatory mixed methods case study, again focusing on the E Alu Pū network. I will use the same survey data and analysis from Study 1 for the quantitative strand. The quantitative results will inform the development of an interview protocol and selection of participants to interview for the qualitative strand. I will conduct interviews and review documents to round out data collection for the qualitative strand. For the integration step of this mixed methods case study, I first will quantize the qualitative data for use with QCA. Then using QCA, I will derive any necessary and sufficient conditions for the desired network outcomes. In the third and final study, I will compare results from the prior two studies to understand what, if anything, using QCA can contribute to collective action networking evaluation.

Figure 3

Procedural Diagram for Three Scaffolded Studies



Study 1: Quantitative Study with Social Network Analysis

As illustrated in Figure 3 above, the first study for this research project involves the same steps, procedures, and products as the quantitative strand of the second study. In this chapter, I will refer to this component of the research project jointly as the “quantitative study.” For the quantitative study, I will use a nonexperimental descriptive design that incorporates archival quantitative survey data. This study answers two questions:

- To what degree are various network structures and relationship characteristics present for the E Alu Pū network and member groups?
- To what degree have intended outcomes been achieved by the E Alu Pū network and member groups?

I have chosen not to use an experimental or quasi-experimental research design, which bears explanation. The purpose of experimental and quasi-experimental research designs, as opposed to descriptive designs, is to infer results from an experiment to a larger population and to statistically determine the relative importance of certain variables in producing certain outcomes. However, the purpose of this study is not to compare the results for one group with another group, nor is it to infer results from this study to a larger population. Even more relevant, data from collective action networks is interdependent and, thus, violates a basic criterion for using most inferential statistics (Bodin et al., 2017; Brandes et al., 2013; Chung et al., 2008; Fredericks & Durland, 2005; Hollstein, 2014; Popeier, 2018). In other words, using most types of inferential statistics to analyze interdependent network data will not produce reliable results. Given this constraint and the purpose for this study, descriptive quantitative data will suffice.

I will analyze the data using descriptive statistics and frequency counts with SNA (also a descriptive quantitative technique). Below, I review the quantitative research design decisions I have made to answer the research questions, including participant selection and sampling, the variables of focus, and data collection and analysis strategies with special attention to SNA.

Participant Selection

Participants in this study are the groups that are members of the E Alu Pū network. The network is comprised of 36 groups that have signed a document called the ʻAe Like to signify their membership. This includes a nonprofit organization called Kuaʻāina Ulu ʻĀuamo (KUA), which acts as the "backbone" support or coordinating organization (Kania & Kramer, 2011). I selected the member groups because they have participated in E Alu Pū and are represented in the archival survey and participation data that will be provided by KUA for this study. In the participation data, member groups are represented by the names of their *poʻo,* or designated representatives for E Alu Pū. While some survey data is anonymous, the survey data to be analyzed with SNA includes the names of *poʻo*, community groups, and stewardship sites. (The *poʻo* who completed a non-anonymous SNA survey in 2021 also provided informed consent under IRB# 1688548-1).

Inclusion and Exclusion

Only groups who are members of E Alu Pū will be included in the study. These are the groups who have signed the ʻAe Like. Groups that have participated in E Alu Pū activities but who have not signed the ʻAe Like will be excluded from the study. Although networks may benefit from partners who sit on the periphery, the network members provide the most complete, most reliable information about whether collective action networking makes a difference.

Participant Characteristics

Most E Alu Pū groups are situated in and represent communities that are predominantly Native Hawaiian or are mixed race with Native Hawaiian as the predominant cultural affiliation.

Though KUA does not ask individuals to report their racial or ethnic identities, the *poʻo* have self-identified as Native Hawaiian, mixed race, Pacific Islander, Asian, white, and more. All the groups are situated in Hawaii, and all the *poʻo* live in Hawaii. Most live in and represent rural, tightknit communities where they have ancestral ties. All the groups and all the *poʻo* are involved in community-based resources management in Hawaii. Some are *limu* (seaweed, or marine algae) practitioners, as *limu* is a food, medicinal, and cultural staple. Others manage traditional Hawaiian fishponds. Still others are nearshore subsistence fisherfolk, while others are taro farmers. Many participants are multifaceted practitioners—a nearshore fisher who also manages a taro patch and hunts, for example. For many participants, it is their cultural and ancestral ties that have led them to engage in traditional and cultural practices of community-based resources management.

Sampling Procedures and Sample Size

The quantitative study centers on a single network with member groups. Because of this laser focus, I am using a census rather than sampling. The goal is to include each of the 36 network member groups in the study. For SNA to work effectively, a clear definition about who is "in" or "out" of the network is needed (Prell, 2011; Yin, 2018). Also, the network should be well-established enough that network members have experienced varying degrees of outcome achievement. Also, understanding a network requires understanding the subunits, or the parts that comprise the whole. A missing network group can radically shift an understanding of the character of the network. Therefore, census sampling of one network (E Alu Pū) and its member groups (36 community groups including KUA as the backbone) is necessary.

Measures and Covariates

Because the network and its member groups—rather than individuals—are the focus of this study, I will not collect individual demographic characteristic data. The covariates (like independent or predictor variables) available through archival and survey data are descriptive member group characteristics reflecting the networking strategies KUA staff use, which are gatherings, workshops, *huakaʻi* (site visits), collective advocacy, direct support through facilitation, and direct technical assistance. Program theory informs these choices. Program theory is the beliefs articulated by network members and KUA staff members that describe how certain activities will lead to certain outcomes (Mertens & Wilson, 2019). The program theory of the E Alu Pū network indicates that by providing networking via gatherings, workshops, *huakaʻi,* collective advocacy, and direct support through facilitation and technical assistance, network member groups will achieve certain outcomes. These covariates are as follows:

- Number of years of participation
- Percent of trainings and workshops attended
- Percent of gatherings attended
- Percent of *huakaʻi* attended
- Degree of facilitation support provided by KUA
- Degree of technical assistance support provided by KUA

Variables

The data I can study using participant and survey archives from KUA include both moderating variables and outcomes variables at the member group and network levels. To frame these variables, I return to the program theory, which indicates that providing networking via the strategies described above will increase the connectivity between network member groups. The greater a group's connectivity, according to program theory, the more likely a group is to achieve the desired site-based outcomes. The smaller the group's connectivity, the less likely a group is to achieve the desired site-based outcomes. (In the program theory, desired site-based outcomes are measured by the adoption of effective community-based resource management practices that have been shown to increase environmental health.) Likewise, according to program theory, providing networking via the strategies described above will result in an increase in overall connectivity in the network, leading to the achievement of network-level outcomes. In the program theory, desired network-level outcomes are measured by advocacy participation and successes.

The member group and network-level moderating and outcome variables are detailed in Appendix B. Briefly, they include subunit moderating variables and outcome variables, and they include network-level moderating variables and outcome variables. The subunit moderating variables are related to network connectivity, which is measured using SNA; organizational capacity, because groups with greater capacity may be more likely to achieve outcomes; and organizational practices, because certain organizational practices may contribute to outcomes. The subunit outcome variables include the outcomes that E Alu Pū members have said they are trying to achieve and established effective community-based resource management practices. Then, the network-level moderating variables are about connectivity, measured using SNA. Lastly, the network-level outcome variables are the network outcomes of interest for E Alu Pū members.

Data Collection

No original data collection will take place for the quantitative study. KUA will provide archival data from a network member survey deployed in January 2021 under IRB# 1688548-1.

The survey, which was distributed via the online platform Survey Monkey, included questions about network members' connectivity to other network members, organizational capacity and practices, and outcomes. Because 36 groups are members of the network, the E Alu Pū Coordinator was striving to collect surveys from all 36 groups. She emailed all members in January with a link to the survey in Survey Monkey and a request to fill it out. She sent two reminder emails to members who had not filled out the survey by the deadline, and the survey was kept open to encourage full participation.

Quality of Measurements

The quantitative data will consist of archival participation and survey data. With documents and archival records, the primary quality concerns relate to omission, errors, and bias, which can be managed to varying degrees. The archival participation data has been tracked since the first E Alu Pū gathering in 2004. To manage errors or omissions in the data, I will cross-check archival records against each other, as KUA has planning and reporting documents for activities. For example, KUA requires waivers for any in-person events, and participants sign in on a physical piece of paper. For any off-island participants, there are records of airline tickets purchased that can be checked against the waivers and sign-in sheets.

The main survey data to be used is from an annual survey deployed to E Alu Pū groups in January 2021. Most of the questions that were included have been used in prior annual surveys and, thus, have been pilot-tested over time. To strengthen the survey, several steps recommended by Fowler (2014) were employed to increase quality of responses. First, a critical review of questions by two qualified individuals using a checklist of standards by Gehlbach and Artino (2018) was meant to detect common survey errors from double-barreled questions to typos. Second, individual cognitive interviews were conducted with three network participants who would not be asked to complete the final version of the survey as part of the census. Reliable survey questions are those that are interpreted the same way by all respondents, so cognitive interviews are used in survey research to discover different interpretations of questions and answer choices among respondents (Fowler, 2014). The survey was input to Survey Monkey, the survey deployment mode that KUA uses. Once in Survey Monkey, the survey was pilot-tested by four people as a final effort to uncover any issues. The survey was finalized in Survey Monkey based on pilot-test feedback.

Instrumentation

Again, KUA gathers data through an almost-annual survey to network groups. Each member group is asked to complete one survey to represent the group. The annual survey for 2020 incorporated questions about member sites (acreage, volunteers, full-time staff, outreach); types and degree of connectivity (using established SNA data collection techniques); perceptions of network health; use of effective community-based resource management practices; and perceptions about KUA staff adherence to its core values. Both closed and open-ended questions were asked. Rating scale questions featured a sliding scale between 0% and 100% rather than scale categories to increase variation in responses (Roster et al., 2015). Survey results will contribute quantitative data about member group and network outcomes (SNA, frequency, and other descriptive statistics).

Conditions and Design

For the quantitative study, I am using a nonexperimental, descriptive design. Further, the study is a naturalistic inquiry, or one in which a researcher examines “real-world situations as they unfold naturally in a nonmanipulative and noncontrolling way, being open to whatever emerges” (Johnson & Christensen, 2017, p. 419). In other words, it is not experimental, and I will not manipulate conditions. The purpose of the study does not necessitate the use of experimental or group-comparison designs. Also, neither random sampling nor random selection is appropriate given the nature of the study, which limits the types of statistical analyses that are advisable to use. Finally, network data is interdependent and violates the criterion for most types of inferential statistics. For all these reasons, a descriptive, nonexperimental approach is best.

Data Diagnostics

Once the archival data is in hand, I will inspect it for appropriate respondents per the inclusion criteria, nonsensical or self-contradictory responses, and missing data. First, I will remove data about groups who are not one of the 36 groups who have signed the E Alu Pū ʻAe Like since those groups do not fit the inclusion criteria of the study. Then, I will flag nonsensical or unclear responses to determine whether the answers can be rectified (i.e., if a respondent typed a zero instead of an "o"). If not, I will remove the nonsensical responses. Most challenging is dealing with missing data from nonresponses. Fowler (2014) suggested that the average response for an item could replace missing data for that item. However, because the census is small, substituting an average that is potentially inaccurate could have large and problematic effects. Although removing the observation is also problematic because of the small census, it is the approach I choose, especially given the purely descriptive nature of the analysis. I will report the percentage of missing data for each item. Also because of the descriptive nature of the quantitative study, I will not perform any data manipulation or transformation.

Analytic Strategy

I will use three strategies to analyze the archival participant and survey data: frequency counts, descriptive statistics, and SNA. Most straightforward will be the analysis of the participation data, which will be accomplished with frequency counts for each group per each type of networking activity (gatherings, workshops, *huakaʻi,* and so on). For survey questions, either frequency counts (for questions such as rating scale questions) or descriptive statistics (for interval/ratio data such as numbers of volunteers) will be appropriate.

More involved will be the analysis of the network using SNA. The purpose of analysis using SNA is to describe the nature of interrelationships comprising the network at both the group member level and the network level. Analyzing social network data in evaluation contexts can facilitate understanding of whether efforts to build relationships have been successful, how connected different network members are to others in the network, who are the key connectors, who are sitting on the periphery of the network, which network members are more likely to disseminate information to others, which members act as connectors, and more.

Social Network Analysis

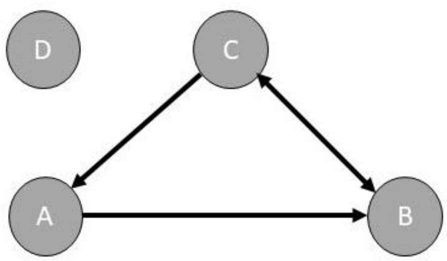
The E Alu Pū survey deployed in January 2021 included questions about connections within the collective action network. Each respondent answered three questions about their relationships with other groups in the network—with which groups their group shared information, worked on projects, and aided when needed. To supplement the SNA questions, KUA provided archival data about how long each group has been a member of the network, how many network events they have attended, and whether the group has participated in any network-wide actions such as public hearings or advocacy events at the legislature. Respondents also answered open-ended survey questions about groups' adoption of any practices or strategies based on their network participation and about progress toward E Alu Pū goals.

Graph theory and matrix algebra come together in SNA to describe patterns of ties between nodes (in this case, network member groups). For example, Figure 4 visualizes a small network of four nodes and three ties: Group A reported sharing information with group B, group

B reported sharing information with group C, group C reported sharing information with groups A and B, and group D neither received nor shared information with the other groups. When graph theory and matrix algebra are applied to patterns of relationships across an entire network, researchers can learn about the connectors, strong and weak ties, cliques, reciprocity, homophily, and more (Bodin et al., 2011; Borgatti & Halgin, 2011). Typically, SNA is used to assess whether collaboration or connection is happening (Birk, 2005; Liou et al., 2015; Munoz et al., 2016; Shadle et al., 2018).

Figure 4

Network of Four Nodes (A, B, C) and Three Ties



Note. This digraph (a graph that depicts directional ties with arrows) displays which nodes share information with the others. The double-sided arrow between Node C and Node B indicate a reciprocal tie, meaning that Node B named Node C in this information-sharing network, and vice-versa. Node D is an isolate, meaning that it shares no information-sharing ties with the other nodes (Durland, 2005; Prell, 2011).

Network theory is focused on the nature of networks, such as how patterns of relationships emerge and what affects the patterns of relationships. The question is whether networks affect ties that are formed or whether networks are a product of ties that exist (Borgatti & Halgin, 2011). Some network researchers, the connectionists, focus on elements that cause networks to take shape differently. Other network researchers, the structuralists, focus on how differences in network structures align with different results (Borgatti & Foster, 2003; Borgatti & Halgin, 2011; Brandes et al., 2013; Fredericks & Durland, 2005). Collective action theory, which focuses on the principles and conditions that promote collective action, better aligns with the structuralists' interests (Ostrom, 2009). Past research on collective action indicated that stronger density and degree centralization of a network was characteristic of more effective collective action (Chen, 2020; Crossley & Ibrahim, 2012).

Based on past research and collective action theory, the network characteristics under review for this study include demographics, indegree and outdegree centrality, multi-relational ties, and overall network cohesion as indicated by density and degree centralization. The definitions and interpretations for these network characteristics are described below (informed by Durland, 2005; Prell, 2011). The characteristics include node-level measures and network-level measures. Node-level measures aid an understanding of the degree to which different groups in the network engage. Network-level measures aid an understanding of the degree of cohesion present in the network (Prell, 2011). To understand a network requires an analysis of node-level and network-level data (Prell, 2011).

Raw data from the survey of E Alu Pū groups will be prepared in an Excel spreadsheet; each tie between two nodes will be listed (see example in Table 1). The data will be analyzed using the open-source software R, for which SNA packages have been developed (Kolacyk & Gábor, 2020). The node-level results will be presented in a table with de-identified data. Network-level SNA measures will be reported and described. A sociogram, or visual representation using a graph like that shown in Figure 4, will be included for the different SNA questions (about sharing information, working on a project together, and trust).

Table 2

Example of Raw SNA Data Showing Connections Between Groups

Originating Node	Tie Named
Group A	Group C
Group A	Group D
Group A	Group F
Group A	Group S
Group B	Group D
Group B	Group H
Group B	Group S
Group C	Group A
Group C	Group D

Network Demographics. A description of network demographics will include the number of groups representing the different islands, how long groups have been operational, how long groups have been members of E Alu Pū, and the degree of participation in network activities.

Centrality. Centrality is a node-level measure of the number of links that pass through a node and thus indicates the node's level of involvement in the network. Indegree centrality indicates the number of times the node was named by others as a tie and so can be a measure of popularity. Outdegree centrality indicates the number of times the node named others as a tie and so can be a measure of friendliness or influence (Durland, 2005; Prell, 2011).

Multi-relational ties. When nodes indicate multiple levels of relationship between one another, they have a multi-relational tie. For example, if Group A reported that they share information with Group B and have worked on a project with Group B, then Group A has a multi-relational tie with Group B. This measure indicates stronger and weaker ties (Prell, 2011).

Cohesion. In network and sociological theory, the concept of cohesion is related to feelings of belonging; cohesion helps to keep actors engaged in a network (Prell, 2011). Network density and centralization are measures of network cohesion. Density is the proportion of possible ties in the network to actual ties (Durland, 2005). "If a high proportion of the potential ties are realized, then the network is considered a dense network, and some would say, a cohesive one" (Prell, 2011, p. 40). Degree centralization helps to address issues with improper interpretation of density. At the network level, degree centralization indicates nodes that are holding a large proportion of the network's ties. Degree centralization can help uncover a scenario in which network measures indicate strong network connectivity that is misleading because only a couple of network members are highly connected, thus skewing the data (Prell, 2011). Therefore, "a network with high density and high centralization would be less cohesive than one with the same density score, but a lower centralization score" (Prell, 2011, p. 40).

In most evaluation and research involving the use of SNA, these SNA results—network demographics, centrality, multi-level ties, and cohesion—would suffice for results. Using these characteristics, researchers and evaluators can describe the structure and relationships of a network. Some researchers have paired data about network characteristics with qualitative data to link network structures to effectiveness or to further describe the case of a network (Coburn et al., 2012). In other studies, SNA data has been used as dependent variables in correlation or regression analysis—a questionable practice given the interdependent nature of SNA data.

Newer SNA techniques such as exponential random graph modeling has enabled inferential statistical analysis to predict network structures (Bodin et al., 2017; Carolan, 2014). Finally, network outcomes have been studied statistically using multi-level models such as hierarchical linear modeling and structural equation modeling, though it is worth remembering that multi-level models function best with larger sample sizes. A handful of studies have used QCA with network studies (Hollstein & Wagemann, 2014). This research will contribute to that discussion. I next will describe the second study, for which I will use an explanatory mixed methods case study culminating in the integration of quantitative data and qualitative data using QCA.

Study 2: Explanatory Mixed Methods Case Study

Study 2, an explanatory mixed methods case study, will describe the case of a single network, E Alu Pū, with embedded subunits, or network member groups. Using an explanatory mixed methods design means that I first will conduct the quantitative strand, already described above as Study 1. Then I will use the results of that quantitative strand in the execution of the subsequent qualitative strand (Creswell & Plano Clark, 2018). The qualitative strand answers these questions:

- For the E Alu Pū network, what intended and unintended outcomes emerge from networking experiences and activities?
- For the E Alu Pū network, what conditions are necessary and sufficient to achieve the intended outcomes?
- How does qualitative data about the E Alu Pū network help to explain or contextualize quantitative survey data about network relationships, structures, and outcomes?

A case study is meant to describe a “phenomenon within its context from a variety of data sources” (Baxter & Jack, 2008). Case study is an appropriate method for situations meeting the following conditions, according to Yin (2014):

- The researcher is not manipulating variables. (I am not.)
- The context is relevant to understanding the phenomenon. (It is.)
- The research question is a *how* or *why* question. (It is.)
- The researcher uses a variety of sources to elucidate and describe the case. (I will.)
- There are unclear boundaries between context and the phenomenon under investigation. (There are.)

Below, I describe exactly how this study aligns with those conditions by elucidating the case study design, beginning with the research setting and case, type of case study, and proposition, followed by detail about the data sources, participants, data collection, and data analysis.

Research Setting & Case

For a case study, the most important early decision a researcher makes is how to bound the case, or unit of analysis (Gerring, 2017; Yin, 2018). The case for this study is E Alu Pū, a collective action network of community-based resource management groups in Hawaii. The network was brought together first in 2003 by an organization now called Kuaʻāina Ulu ʻAuamo (KUA). KUA responded to a suggestion by an elder fisherman that Hawaiian island communities isolated from one another should be brought together to share and perpetuate traditional and contemporary strategies for resource management (Kuaʻāina Ulu ʻAuamo, n.d.a). The network has grown from 12 community groups represented at the 2003 gathering to 36 community groups that are signatories of the E Alu Pū ‘Ae Like membership agreement as of January 2021 (A. Connelly, personal communication, December 1, 2020).

Though non-member groups sometimes participate in E Alu Pū activities, the unit of analysis for this case study will be bound by the criteria of current E Alu Pū membership. “Membership” is defined as those groups that are signatories of the ‘Ae Like as of January 1, 2021. These groups comprise the current active network that is the focus of the study. That is, they receive communications from KUA, are invited to participate in network events and activities including gatherings and workshops, have tools and resources from KUA at their disposal, and are supported by network coordination and facilitation.

The E Alu Pū Council, comprised of elected members representing the different islands, provides governance for the network. KUA facilitates and coordinates the Council and the network. KUA, which roughly translates to “backbone” (Kua‘āina Ulu ‘Auamo, n.d.b) is a backbone support organization, one of the essential elements of success for collective action networks, according to Kania & Kramer (2011). KUA manages the essential functions that hold the network together, freeing the network members to focus on site-based and collective work toward their shared goals. KUA staffs an E Alu Pū coordinator, responsible for gatherings and workshops, Council meetings, network communications, and more. With guidance and support from the Coordinator and Council, the network has matured from a learning network to a collective action network that pursues a common agenda for social change (Ernstson, 2011). The network’s overall vision is *‘āina momona*, which literally translates to “fat land” and which generally is translated to mean “abundance.”

Type of Case Study

Using Yin's (2018) case study typology, the type of case study I will conduct is an explanatory case study. This is distinct from an explanatory mixed methods study, which explains quantitative data collected initially with qualitative data collected secondarily. An explanatory case study is meant to link program activities to outcomes (Yin, 2018). Technically, then, this study is an explanatory mixed methods explanatory case study. For the case study, I will focus on a single case, E Alu Pū, with embedded subunits, the network member groups.

To further explain, I have chosen to conduct an explanatory case study because the question I am trying to answer is about the outcomes that emerge from networking activities. In other words, I am trying to establish whether there is a link between networking and outcomes, which is what an explanatory case study is designed to do (Yin, 2018). Based on experience, literature about community-based resources management, and the program theory, possible outcomes of collective action networking within the context of this case have been identified previously (Blythe et al., 2017; Curtis et al., 2014; Gruber, 2010; KUA, n.d.c; Lozano & Heinen, 2016; Murphree, 2009; Sterling et al., 2017). Using those identified outcomes and an explanatory approach, I will be seek to uncover outcomes of networking.

Also, the study will focus on the case of one network with embedded subunits, what Yin (2018) calls an embedded case study. There are a couple of reasons for using an embedded approach. First, doing so will ensure a smaller, more focused study than would be possible with multiple networks. Networks are comprised of multiple people or groups, so adding more networks would generate exponentially more data and complexity, potentially to the point of meaninglessness. The second reason for using an embedded approach is that the variation in participation and outcomes is necessary to answer the research question about whether engagement in networking contributes to outcomes. If the case study focused on one case without subunits, no variability would exist. A single, embedded case provides the benefit of focusing the study while still yielding the necessary variability to answer the research questions.

Proposition

Just as an embedded case with subunits helps to focus a case study, so does the use of a proposition. In case study research, the term "proposition" is used in a similar way that "hypothesis" is used in quantitative research (Yin, 2018). A proposition helps to focus a case study (Baxter & Jack, 2008) and is often used in evaluation contexts to help determine what types of outcomes emerged from an intervention (Yin, 2018). For this study, the proposition is that collective action networking contributes to outcomes. The proposition arises from experiences of collective action networks, prior research, social science theory, and program theory (Alexander et al., 2018; Bodin et al., 2017; Cabaj & Weaver, 2016; Ennis & Tofa, 2020; Ernstson, 2011; Groce et al., 2019; KUA, n.d.c; Lawlor & Neal, 2016; Maglajlic & Helic, 2012; Maroulis & Gomez, 2008; Ostrom, 1990; Ostrom, 2009; Plastrik et al., 2014).

Data Sources

The decisions to use a single embedded case with an explanatory case study directly affect the remaining case study design choices. Before describing the participants from the case and the process of data collection and analysis, I first describe my own positionality as a researcher. Because in qualitative research, the researcher is like an instrument and data source, my identity, experiences, and perspective affect every aspect of the study, from my relationship with participants to my interpretation of results (Patton, 2015). From my description of myself as a researcher, I then describe other data sources, data collection, and data analysis to round out the qualitative strand of this explanatory mixed methods case study.

Researcher Description

My relationship with E Alu Pū began in 2004, almost at its beginning, and has continued unbroken since then. Briefly a volunteer, then program staff, then director from 2006 through 2011, I co-founded the organization now known as KUA. Since 2012, I have continued to work with KUA as a consultant with a primary focus on evaluation. As director and then as evaluator, my burning question has been the question at the heart of this study: Does networking make a difference? It is the question that drove me to return to graduate school and to specialize in evaluation. It is the question that frustrated me as I took statistics classes and learned that networks confound the criteria for interdependence that is foundational for traditional inferential statistics. It is the question that led me to search for research strategies befitting smaller groups. Training in and use of SNA served to answer only part of the question. After many years of searching for appropriate tools, I learned about QCA. Two intensive back-to-back one-week courses in SNA and QCA encouraged me to combine the two methods to see if I could finally discover the long-pursued answer to the question of whether collective action networking makes a difference.

My identity affects my understanding of this and any research. As a white woman in mid-life with a master's degree and a PhD pending the satisfactory completion of this research project, I am a member of a highly privileged group. I am not Hawaiian, not a traditional Hawaiian knowledge expert, nor a practitioner of community-based resources management. I have not lived the experience of being crowded and forced out of the places of my ancestors with policies that enable stolen land and continued military occupation while privileging the desires of tourists, vacation homeowners, and developers.

My guiding policy is to work only where I am invited, and KUA and E Alu Pū continue to invite me. KUA is interested in the outcome of this research project because they are interested to know whether QCA with SNA provides a better answer to our shared question about networking and outcomes. During this study, I will incorporate practices consistent with credible and trustworthy qualitative research with the intent to ensure the relevance and accuracy of the research to E Alu Pū and KUA (Treharne & Riggs, 2014). I will regularly consult with the KUA staff including the E Alu Pū Coordinator to ensure the project is relevant to KUA. I also will consult with the E Alu Pū Council before, during, and after data analysis to ensure the project is relevant to KUA. I will engage both groups in interpretation of the data to limit intrusive effects of my own identity on the analysis and interpretation of results.

Participants

Participants in this study will be representatives of the 36 network member groups of E Alu Pū, including KUA, along with closely aligned network stakeholders. Most E Alu Pū groups identify as Native Hawaiian and share a common interest in perpetuating cultural and traditional resource management practices. Before Western contact, the Hawaiian Islands were home to about the same number of people who are residents of Hawaii today (McClenachan & Kittinger, 2012). Even so, research using modeling suggested that Native Hawaiians caught about 50% more fish prior to Western contact than modern fleets catch today (McClenachan & Kittinger, 2012). They did this sustainably for hundreds of years. Resource management was decentralized, relying on local, intimate knowledge of resources (Jokiel et al., 2011). The members of each *ahupuaʻa* (traditional Hawaiian land division roughly equivalent to a watershed) took responsibility and had authority to care for the natural resources upon which they relied (Jokiel et al., 2011). Since Western contact in 1788, the illegal overthrow of the Hawaiian Kingdom by the

United States in 1893, and contemporary state-controlled management based on the concept of common-pool resource use (Ostrom, 1990), fisheries in Hawaii have declined precipitously (Jokiel et al., 2011). E Alu Pū seeks a return to effective community-led resources management that holistically promotes communities' desire to practice culture, harvest healthy and plentiful food, and sustain the relationship between people and between people and place. To achieve this, the goals of E Alu Pū, determined collectively by network member group participants using empowerment evaluation (Fetterman, 2014), are as follows:

- Increase community voice in resources management.
- Perpetuate traditional Hawaiian resource management practices.
- Effectively manage the natural and cultural resources at community-based sites.
- Speak together as one to change systems affecting natural and cultural resources.

Each network member group is comprised of multiple individuals. This study does not target the individual level, however, but the group level. Each E Alu Pū group has assigned a representative, called a *poʻo* (leader; wehewehe.org). The *poʻo* agree to represent the will of their groups by discussing decisions and carrying the will of the groups forward to E Alu Pū. KUA is represented in E Alu Pū by the E Alu Pū Coordinator. The *poʻo* primarily interact with other *poʻo* and, thus, are the conduit for connection throughout the network. They are asked to complete and submit an annual survey to the E Alu Pū Coordinator, and they are the main points of contact for questions and conversations relevant to the network and their community-based sites. Because of the role the *poʻo* play in E Alu Pū, they will be asked to represent their groups as participants for this study.

Another important voice in the study will be closely aligned stakeholders. For example, E Alu Pū has benefitted from the investment of several core partners, including foundations that have provided funding consistently since 2003. One can assume that these investors in the movement have remained committed because they perceive the achievement of certain outcomes or benefits. In addition to funders, staff at resource management agencies or organizations have worked with KUA in various capacity through the years. Including their voices in the study will close gaps in understanding the link between networking and outcomes.

Documentation and Archival Records

In addition to participants discussed above, archival KUA and E Alu Pū documents will act as the final sources of qualitative data. Since E Alu Pū was founded in 2004, reports have been written about events such as gatherings and workshops, evaluation reporting began 2008, and grant reporting began with the first grant received. These reports will provide de-identified data about network members' experiences with the network. Also, in 2016, the network coordinator began making annual phone calls to each network *poʻo*, and de-identified thematic results from those discussions also will speak to network members' perceptions of the network. Additional KUA documents such as staff meeting notes will provide context and detail.

Researcher-Participant Relationship

As described above, I have had a long-term relationship with the E Alu Pū network, having co-founded and directed the organization and having been a consultant since 2012. In 2017, I worked with the E Alu Pū Coordinator to facilitate an empowerment evaluation (Fetterman, 2014) process that led to the establishment of shared goals and measures for E Alu Pū. I had direct contact with E Alu Pū group representatives and the E Alu Pū Council during this process. I also have created the surveys used to evaluate network gatherings and workshops, in addition to the almost-annual surveys used to inform work planning for KUA and action strategies for E Alu Pū. Although network member groups who joined E Alu Pū after 2011 do not know me well and may not be aware of my past role as co-founder and director, most groups have heard my name and know that I am connected to KUA. Because of the growth of the network over time, the groups who know my history comprise less than half of the network today.

I am separated from the network by geographic, temporal, cultural, and relational distance, so participants may not feel pressure to provide answers I might want to hear as they might with someone they know very well. At the same time, KUA staff members speak about me as a part of their team, so network group members do not distrust me as they might an outsider new to the network. That may affect their willingness to participate in the study once recruitment begins, which I discuss next.

Participant Recruitment

I considered working with four different networks for this study. After discussing the potential study with three network coordination teams and completing background research about all four, two were considered viable candidates. The viable candidates were active in content areas in which I had some expertise, and they were well-established enough networks that it was likely that network groups had varying degrees of success in achieving outcomes. I presented information about the potential combination of SNA and QCA to KUA staff members, who consistently have expressed curiosity about evidence that can help them assess their networking strategies, during an in-person work-planning staff retreat in January 2020. KUA staff members agreed that they would like KUA to participate in this research. Because E Alu Pū is the most well-established network that KUA facilitates and because the E Alu Pū Coordinator was confident that network members would be willing to provide the needed information, I selected E Alu Pū as the case for this research.

Recruitment Process

Since the case network was determined, all 36 network member groups will be included through the archival records and documentation provided by KUA, which generated and owns the data. Based both on the quantitative study results and the historical documents from KUA, I will develop a list of potential interviewees and discuss them with KUA staff. To develop the initial list, the results from the quantitative study will inform the selection of participants. First, recruitment of network member groups will be determined according to the quantitative data based on three dimensions: variation in participation, connectivity, and outcomes. In other words, I will interview member groups for which the data indicate higher and lower participation according to the archival participation data, stronger and weaker connectivity according to results from SNA, and greater and lesser achievement of outcomes according to the quantitative results. It is likely that member groups will represent these dimensions in complex ways. For example, a group may have had high participation during certain years and low participation in other years, or a group may show weaker connectivity and greater achievement of outcomes. I will consider variation within groups and variation between groups as I select interview participants. Further, I will catalogue and discuss the three dimensions of variation with each group. Directed by this variation, I will interview the *poʻo,* or leaders, of these network member groups, including the E Alu Pū Coordinator.

Additional stakeholders such as foundation staff, agency staff, policymakers, and organization partners also will be selected for interviews. I will choose these stakeholders based on variability in the type of organization and the length of their relationship to KUA and E Alu Pū, which represents degree of investment in networking.

For the potential participants that I know personally, I will email them with a request to participate in an interview. I will explain the purpose of the interview in the email and will include a link to an electronic consent form. For the potential participants I do not know personally, the E Alu Pū Coordinator will ask permission via email to connect us. For those that consent to be connected, the Coordinator will introduce us over email. From there, I will email to request their participation in an interview, explain the purpose of the interview, and include a link to an electronic consent form. (See Appendix C for information about the Institutional Review Board approval for this study.)

Participant Selection

From the participants who agree to participate, I plan to interview between eight and fifteen, though this could expand or contract based on saturation, the situation occurring when no additional themes are uncovered by additional interviews (Creswell, 2012). I will use purposive variation sampling, which means I will select interviewees who represent groups with variation as described above (Patton, 2015). For network member groups, I will look at the data from the quantitative study for variation in groups' participation in and connectivity within the network and variation in the outcomes their groups have achieved. For other stakeholders, I will look at data from KUA documents and interview participants from different types of agencies and with different histories with E Alu Pū and KUA. The reason for variation sampling is to capture and represent different perspectives about the value of networking and different perceptions about the outcomes that emerge from networking. For example, if I spoke with *poʻo* who all are highly connected to and engaged in the network, I likely would hear positively skewed information about the value of networking. I also will interview the E Alu Pū Coordinator.

Data Collection

Case studies typically draw data from multiple sources. Yin (2018) named documentation, archival records, interviews, observation, participant observation, and physical artifacts as common sources of evidence used in case studies. For this case study, I will collect data from documents, archival records, and interviews. (See Appendix D for the data collection logistics table.) Though my original plans included data collection through observation and participant observation, these plans were thwarted by the COVID-19 global pandemic.

Setting and the Effect of COVID-19 on Data Collection

Given the importance to case study research of studying a case within its real-world context (Yin, 2018), I originally designed this study to include in-person interviews, site observation, and participant observation of E Alu Pū gatherings and events. In-depth in-person discussions and observations could have produced nuanced data about each subunit that could have been used to develop a more refined assessment of conditions and outcomes for each. The COVID-19 pandemic irretrievably affected gatherings, travel, and in-person data collection, forcing virtual data collection. Because of restrictions related to the pandemic, I will use archival documents and interviews to be held over Zoom. Even though data collection will be conducted virtually, I will strive to maintain the quality of real-world context. All E Alu Pū groups were affected by the pandemic, and network activities moved online in March 2020. Virtual data collection became just another adjustment to the real-world COVID-19 context for E Alu Pū.

The one element I will not be able to reproduce well in a virtual environment are the network gatherings and workshops, which are activities for which the network has traditionally come together about twice per year. All network activities were conducted online beginning in March 2020 at the beginning of the pandemic, and KUA staff will continue with virtual-only events through the foreseeable future. To replace the in-person observation I had hoped to implement, I will use reports from past events that include photos and videos.

Data Collection Procedures

Interviews. I will conduct semi-structured interviews with eight to fifteen participants, including (1) *poʻo* representing groups that have participated in and connected with the E Alu Pū network to varying degrees and achieved varying degrees of outcomes, and (2) stakeholders who represent different organizations that have varying relationships with E Alu Pū. The purpose of using interviews rather than another approach such as focus groups is to understand more deeply and richly the variability in what network participants perceive as the value and benefit of networking, whether their perceptions align with the intended outcomes or surface different outcomes. I will use a semi-structured interview protocol, for which I have developed a draft (Appendix E) but will update based on results from the quantitative study. I will conduct interviews using Zoom and will record them, pending permission from each interviewee. Zoom can produce transcripts from recorded interviews, which I will correct using the recordings. Given the iterative nature of qualitative research, I will borrow from phenomenology and conduct follow-up interviews as needed with participants from whom I seek clarification (Creswell, 2013). After each interview, I will respond reflexively, which Patton (2015) describes as deep, systematic awareness and reflection (p. 70). Each reflexive response will be paired with the corresponding interview transcript.

Documentation and Archival Records. KUA has created reports from gatherings (36 reports), emails from KUA to E Alu Pū (archived from 2015 through 2020), archived data from annual surveys (6 surveys between 2013 through 2020), staff meeting notes (archived from 2019 and 2020), staff updates about activities related to the desired outcomes (archived from 2017 through 2020), and themes from the Coordinator's annual phone calls to the *poʻo* (archived from 2017 through 2020). All the documents and archives are stored on a Google Drive shared just with KUA staff and selected contractors. To carefully track the research pathway for others to follow, Yin (2018) suggested that case study researchers create a bibliography of documents. I will follow this recommendation, entering each record into a database including a number for the record, the name of each file, where the document is stored, the date the document was generated, the date of observations/event, person(s) who contributed to the document, the subject matter it contains, and my reflexive response to the document.

Data Analysis

Data analysis will consist of multiple rounds of thematic analysis with each record, reflexive response during analysis, pattern-matching to determine whether the proposition that collective action networking contributes to outcomes is supported by the data, and thematic analysis of the reflexive data to understand how my perspective may affect the analysis. In addition to reflexivity, I will employ several strategies, described below, to ensure methodological integrity.

Data-Analytic Strategies

As I collect the qualitative case study data, I will analyze it during multiple rounds with each record. First, I will use constant comparative thematic analysis, a type of inductive qualitative analysis for which "the researcher simultaneously codes and analyses data in order to develop concepts; by continually comparing specific incidents in the data, the researcher refines these concepts, identifies their properties, explores their relationships to one another, and integrates them into a coherent explanatory model" (Taylor & Bogdan, 1984, p. 126). Beginning with this inductive approach will surface concepts from the data without constricting them to specific, predetermined codes or categories (Creswell, 2012). Data is compared with other data with constant comparative analysis, seeking whether new information aligns with the concepts that are forming (Taylor & Bogdan, 1984).

While constant comparative analysis typically is associated with grounded theory, Fram (2013) described using constant comparative analysis deductively with a conceptual model or framework. In that case, the researcher "during the theoretical coding stage, uses such an understanding [of a concept in the framework] to find evidence in the data that reflects this understanding" (Fram, 2013, p. 4). Spring-boarding from that idea, I will review the data during a second round of constant comparative analysis, seeking evidence that reflects the program theory for networking at KUA.

During both rounds, I will employ reflexive writing to my reactions to and perceptions of the data. As Patton (2015) wrote, "Reflexivity reminds the qualitative inquirer to be attentive to and conscious of the cultural, political, social, linguistic, and economic origins of one's own perspective and voice as well as the perspective and voices of those one interviews and those to whom one reports" (p. 70).

From these inductive and deductive rounds of analysis and with the resulting concepts I find, I will move into pattern-matching, a process of comparing what emerged from the data with the patterns expected from the proposition that collective action networking contributes to outcomes (Yin, 2018). The result of pattern-matching should be the identification of patterns that align with the proposition, patterns that do not align with the proposition, and the absence of expected patterns (Yin, 2018). In addition, I will thematically analyze the reflexive data as a companion to the data from interviews, documents, and archives. The purpose of analyzing the reflexive data is both to support awareness of how my perspective may have influenced analysis and interpretation and to “communicate authenticity and trustworthiness” (Patton, 2015, p. 75), which is important to methodological integrity.

Methodological Integrity

To demonstrate that the findings from this study are warranted, I will employ several strategies that provide quality control for interviews and for the review of documents and archival records. I also will use several techniques commonly recommended for qualitative and case study research, described below.

First, the quality of interviews rests with several factors, including rapport, linguistic appropriateness, and proper interpretation (Roulston, 2010). Through a background in journalism followed by community development, I have 30 years of interviewing experience and have developed rapport-building qualities. Also beneficial to rapport-building, the interviews are built on the foundation of my long history with E Alu Pū; I will not be a stranger. That history also supports the development of linguistically and locally appropriate questions.

That history does not eliminate my outsider status, however. To address this, a KUA staff member will review the interview protocol developed and provide feedback about linguistic norms. Then throughout each interview, I will seek clarification and understanding to ensure that my interpretations are accurate (Roulston, 2010). Through these steps, the interviews should elicit the information needed to contribute to understanding. Reflexive journaling directly after each interview will capture thoughts and reactions that might influence analysis (Roulston, 2010). For transparency, transcripts will be created, offered to interviewees for their review and correction, and then de-identified so that they are available for others who want to judge the quality of the interviews (Roulston, 2010; Yin, 2018).

Next, the primary quality concerns with documents and archival records relate to omission, errors, and bias, which can be managed to varying degrees. Documents are produced for a purpose other than research, and they may not contain the naked truth (Yin, 2014). Yin (2014) suggested that case study researchers consider the purpose of each document and filter the information therein through the lens of that purpose. To manage errors or omissions in the data, I will cross-check archival records against each other through constant comparative analysis.

Overall, the quality criteria I will use are credibility, trustworthiness, and confirmability. Credibility in qualitative research has been considered the parallel to internal validity in quantitative research, meaning that the results are trustworthy (Patton, 2015). To enhance credibility or validity, I will use the tools of triangulation, the inclusion of multiple viewpoints, participant engagement, and reflexivity (Patton, 2015; Treharne & Riggs, 2014; Yin, 2018). Triangulation from multiple sources of evidence to establish a convergence of ideas increases construct validity through "multiple measures of the same phenomenon" (Yin, 2014, p. 121; also see Patton, 2015). In other words, using multiple sources of evidence results in "the development of *converging lines of inquiry"* (Yin, 2014, p. 120). In much the same way, using multiple sources of evidence increases construct validity (Patton, 2015). In this case, the multiple sources of evidence will be KUA staff, network member group representatives, aligned stakeholders, archival records, and documents. Participant engagement through member-checking and providing interview transcripts helps to ensure that findings and interpretations accurately reflect participants' understanding. While providing transcripts to interviewees helps to ensure accuracy, member-checking is a process that increases credibility through soliciting participant feedback about the results and conclusions of a study so that they may provide contextual information, cultural interpretation, even correction (Creswell, 2013). To complete member-checking, I will facilitate a discussion about initial results with KUA staff members first, and then with network member groups using modes that they request (presentations via Zoom, for example). Finally, reflexivity helps to build trustworthiness and can raise awareness of bias (Patton, 2015).

Also to combat bias, or looking for what you hope to find, Yin (2014) suggested that case study researchers secure assistance from two or three "critical colleagues" to offer outside opinions about what the understanding of the case the researcher is developing during data collection (p. 76). Built into the dissertation process is the review of the work by multiple experts, which surfaces alternative lines of inquiry and interpretations that contributes to credibility (Patton, 2015, p. 668).

For the quality criteria of confirmability, I will incorporate Yin's (2014) suggestion to develop a case study database to track all activities, documents, reflexive responses, and notes as a "chain of evidence" (p. 127) that would enable a different researcher to follow my path from questions to conclusions. This supports the reliability of the case study (Yin, 2014).

Finally, some would argue that my experience with and knowledge about the case is an advantage (Eisner, 2017; Mello, 2020). Others might argue that my experience with the case produces an unmanageable amount of subjectivity. Patton (2015) argued, "Philosophers of science now typically doubt the possibility of anyone or any method being totally 'objective'" (p. 725). I will strive to be truthful and fair rather than totally objective. Using the quality-control methods described above will help me to produce meaningful, credible results.

Now that I have thoroughly described the procedures for the qualitative strand of the explanatory mixed methods case study, I will turn to an overview of integration in mixed methods. From there, I will review QCA and provide a detailed description of how QCA will be utilized in this study to integrate the quantitative and qualitative data.

Integration of Quantitative and Qualitative Data

In mixed methods research and evaluation, quantitative and qualitative data must be integrated before interpreting results (Creswell & Plano Clark, 2018). Bazeley (2010) defined integration as "the extent that different data elements and various strategies for analysis of those elements are combined throughout a study in such a way as to become interdependent in reaching a common theoretical or research goal, thereby producing findings that are greater than the sum of the parts" (p. 432). Without integration, the quantitative and qualitative results are unconnected. The purpose of integrating the quantitative study and qualitative strand is to develop an in-depth description and understanding of the case and its complex, multifaceted characteristics using both types of data (Creswell & Plano Clark, 2018). Integration will help to answer these research questions:

- For the E Alu Pū network, what conditions are necessary and sufficient to achieve the intended outcomes?
- How does qualitative data about the E Alu Pū network help to explain or contextualize quantitative survey data about network relationships, structures, and outcomes?

To answer these questions, I first will cross-tabulate the patterns and themes from the case study with the descriptive quantitative results. The cross-tabulation, illustrated with a joint display, will reveal where the quantitative and qualitative data produced similar results and areas where different results emerged or even disconfirmed the other (Creswell & Plano Clark, 2018). To be more specific, the joint display will pair quantitative results with direct quotes or summaries of qualitative data that provide support and context for the quantitative results or that differ from the quantitative results. Interpretation of the results will include considering how the qualitative data help to explain or contextualize the quantitative results about the relationships, structures, and outcomes of E Alu Pū.

Most evaluators or researchers using a case study design with SNA would stop here. Going further, however, I will quantize the qualitative data, a necessary step to prepare the data for use with QCA. Then I will integrate the quantitative data, including the SNA results, with the quantized qualitative results. Greater detail about these integration processes follows.

Methodological Integrity for the Case Study

For the integrated findings of the case study to be warranted, I will utilize a handful of strategies to increase methodological integrity. Creswell and Plano Clark (2018) discuss validity threats to both explanatory mixed methods studies and mixed methods case studies, and they provide techniques purported to alleviate those threats. I will incorporate the following techniques:

- Design the qualitative strand to provide context and explication of the quantitative strand.
- Use the quantitative results for selection of the qualitative strand participants.
- Address results that are contradictory through returning to the data to recheck the analysis.
- Bound the case tightly and clearly.
- Interpret the case using the integrated quantitative and qualitative results rather than results from one or the other.

Mixed Methods Integration Using Fuzzy Set QCA

QCA has been hailed as a fundamentally integrative method because both quantitative and qualitative data are used in the same algorithm that produces the analysis (Bazeley, 2010; Hollstein, 2014). During case study analysis, researchers can search for patterns, build explanations and alternative explanations, use logic modeling to link activities to outputs and outcomes, and use cross-case analysis to tease out the common results (Yin, 2018). QCA is a combination of these. Researchers establish the conditions based on understanding of the cases including activities, outputs, and outcomes; applying the algorithm across subunits results in patterns of conditions that are associated with an outcome. Clearly, QCA does not offer something brand new, but it "renders them explicit, standardizes them, and offers a powerful analytical instrument" (Hollstein & Wagemann, 2014, p. 246).

Introduction to QCA. QCA is a comparative analysis method based on Boolean algebra, set theory, and the logic of agreement and difference in which necessary and sufficient conditions are framed as relationships between sets (Hollstein & Wagemann, 2014). QCA can be used to establish causal pathways for small and medium sample sizes and with both quantitative and qualitative data (Kahwati & Kane, 2020; Mello, 2020). The method can be used in situations of causal complexity including when there are multiple combinations of conditions that lead to an outcome (i.e., conjunctural causation); when there are multiple pathways that lead to an outcome (i.e., equifinality); and when different conditions lead to an outcome when compared with conditions that lead to a non-outcome (i.e., causal asymmetry) (Hollstein & Wagemann, 2014; Mello, 2020). These causally complex situations are especially difficult for traditional variables-based inferential statistics to handle, which is one reason that social scientist Charles Ragin was motivated to develop QCA in the 1980s.

Ragin (1987) envisioned QCA existing outside of the paradigm debate of quantitative versus qualitative. The analysis is completed via an established algorithm and tests of fitness that require quantization of qualitative data, characteristics that evoke quantitative statistical techniques. It is worth repeating Hollstein and Wagemann's (2014) reminder that "Boolean algebra places a greater emphasis on the *qualis* (Latin for 'how is it?') of a phenomenon than on its *quantum* (Latin for 'how much is it?')" (p. 249). The techniques used in QCA are meant to "reduce complexity and thereby contribute to a better understanding of the pattern under analysis" (Hollstein & Wagemann, 2014, p. 248). In other words, QCA is a tool to help researchers uncover patterns that elucidate a case. The critical characteristic of QCA is that is rooted in the researcher's case knowledge based on careful case examination and theory (Hollstein & Wagemann, 2014; Mello, 2020; Ragin, 1998). This characteristic, in addition to the practice of repeatedly updating the analysis based on what has been learned and its fundamental focus on different explanations for causes, evoke qualitative traditions. Hollstein and Wagemann (2014) summarized the position of QCA in the qualitative/quantitative paradigms this way: "In contrast to other mixed methods designs, it not only combines several methodological approaches but also borrows principles from various methods in order to arrange them into a new methodological strategy. As such, QCA is an integrated mixed method" (p. 249).

The basic use for QCA is to discover the conditions that are present with a certain result, based on criteria that the researcher elevates from situational and theoretical knowledge. If everyone who has achieved an outcome has completed Task A and everyone who has not achieved the outcome has not completed Task A, then logically, we could conclude that Task A is a necessary condition for achieving the outcome. For example, completing required coursework in a PhD program is usually a necessary condition for achieving the outcome of earning a doctorate degree. However, not everyone who completes the required coursework obtains a PhD degree. The condition of completing required coursework, therefore, is a necessary condition but not a sufficient condition. Additional conditions are required.

Process of QCA. The QCA process for determining which conditions are necessary and/or sufficient for a result was originally established by Ragin in the 1980s. Though researchers since then have developed new techniques that have helped to expand the usefulness of QCA, its basic logic remains intact. Essentially, a researcher using QCA must have significant knowledge of the context, including the outcomes of interest and different conditions thought to contribute to the outcome (Ragin, 1987; Mello, 2020). The researcher gathers data about different cases, some of which have achieved the outcome and some of which have not. This variation is essential to uncover which conditions were necessary or sufficient to the outcome (Ragin, 1987; Mello, 2020).

After the researcher has data that includes the needed variation, a process called calibration is completed (Kahwati & Kane, 2020; Mello, 2020). Effective calibration requires the researcher's substantive and theoretical knowledge, as it is a process of determining how thoroughly the case exhibits each condition. The most common strategies for calibration in QCA are crisp-set QCA (csQCA) and fuzzy-set QCA (fsQCA) (Kahwati & Kane, 2020; Mello, 2020). Crisp-set QCA, the original approach to QCA developed by Ragin (1987), treats each condition as dichotomous. Using attainment of a doctoral degree as an example again, a researcher might determine that only students who have completed 100% of required coursework are members of a condition set called "completion of coursework." Students who have completed anything less than 100% of coursework are not members of that condition set.

Not all conditions are so easily dichotomized, however, which is why fsQCA was developed. For example, if a researcher has decided to use “regular exercise” as a condition to losing weight, that researcher will have to determine, based on prior research, what constitutes membership in the set of “regular exercisers.” Perhaps the researcher will decide that 120 minutes of exercise per week constitutes full membership in the condition, whereas 90 minutes constitutes partial membership and less than 60 minutes constitutes no membership. Using fuzzy-set QCA, set membership in a condition can be more nuanced. Mello (2020) urged researchers to use fuzzy-set QCA over crisp-set because the binary nature of crisp sets tends to oversimplify, resulting in larger set membership. While crisp sets should be used when appropriate for the data, fuzzy sets are preferred when possible because they reflect greater complexity and nuance in set membership (Mello, 2020; Schneider & Wagemann, 2010).

With the process of QCA calibration, each condition can subsume multiple criteria for set membership, including both quantitative and qualitative data (Kahwati & Kane, 2020; Mello, 2020). Researchers and evaluators must clearly state the criteria they use, which should be justifiable based on substantive and theoretical knowledge (Ragin, 1987). Traditional qualitative researchers and traditional quantitative researchers react squeamishly to calibration (De Meur et al., 2012; Ragin, 2005). Qualitative researchers balk at the idea of quantizing qualitative data (Patton, 2015), and quantitative researchers balk at the idea of the researcher’s subjective determination of criteria setting and the use of qualitative data (Sager & Andereggen, 2012). Mixed methods researchers, on the other hand, see combining the two as “an intuitive way of doing research that is constantly being displayed throughout our everyday lives” (Creswell & Plano Clark, 2018). Essentially, fuzzy-set calibration is a more systematic, deliberate, transparent way of organizing information into an ordinal scale.

Once calibration is complete, the researcher creates what is called a “truth table,” a term that sets some people on edge (Kahwati & Kane, 2020). The controversial name notwithstanding, a truth table is essentially a matrix showing the degree to which each case has membership in which conditions. As an example, Table 3 is a fictional truth table of people who have and have not achieved the outcome of doctoral degree and their degree of membership in those conditions. The table illustrates that completion of coursework, successful dissertation proposal, successful dissertation defense, and submission of graduation paperwork are all necessary conditions of earning a doctoral degree. Everyone with a doctoral degree had membership in all those conditions. But those conditions, individually, were not sufficient. From this truth table, we can conclude that all the conditions are necessary but were not sufficient for membership in the outcome of “doctoral degree.”

Table 3

Fictional QCA Truth Table for the Outcome of Achieving a Doctoral Degree

	Completed coursework	Successful dissertation proposal	Successful dissertation defense	Submission of graduation paperwork	Doctoral degree
Chase	1	1	1	1	1
Keani	1	1	0	0	0
Maya	1	1	1	1	1
Joy	0	0	0	0	0

For this study, each condition will be calibrated based on a five-level rating scale for use in fuzzy-set QCA. Details about how outcome and contributory conditions were identified and calibrated, and how set membership will be determined, follow.

Study Outcomes. E Alu Pū members have determined what outcomes they seek to achieve from coming together as a network. This study will focus on three outcomes: (1) E Alu Pū groups are decision-makers in resource management in Hawaii; (2) E Alu Pū groups are effective managers of natural and cultural resources; and (3) E Alu Pū groups display support and solidarity for one another. These outcomes are tracked on a site-by-site basis and for the network overall. For the purposes of QCA, only the site-level information will be utilized. QCA requires comparison, and E Alu Pū is only one network. Therefore, outcomes will be assessed based on site-level achievements. For each desired outcome, E Alu Pū and KUA have identified evaluation measures or indicators based on the groups' experiences, cultural values, and the feasibility to assess indicators. These indicators, in large part, align with collective action theory and empirical research, and they align with research about effective community-based resources management. Appendix F displays the indicators associated with each desired outcome and the prior research that has informed those indicators.

The literature about community-based resources management cites additional outcomes, especially increased native biodiversity and biomass (Dressler et al., 2010; Guber, 2010; Murphee, 2009). Many variables contribute to environmental change, and E Alu Pū groups have limited control over many of those. Groups also have limited capacity to monitor and research vast environmental variables. E Alu Pū groups have decided to focus on the outcomes they have developed because they are actively working together toward those outcomes and because they can evaluate their progress toward those outcomes (again, refer to Appendix F). To assess the degree to which each group has achieved each of the three outcomes, the indicators for the outcome will be compiled (Kahwati & Kane, 2020). For example, for the outcome about decision-making, each of the three indicators have a maximum value of 100%. For each group, an average value for decision-making across the three indicators will be calculated and rounded as needed. Groups will be assigned values based on the following criteria:

- 0%-15% will be assigned a score of 0, meaning fully out of the membership set.

- 16%-49% will be assigned a score of 1, meaning more out than in the membership set.
- 50% is a crossover point. If a group's decision-making value falls at exactly 50.00%, substantive knowledge of the case will be applied to determine whether the group is more in or more out of the membership set (Kahwati & Kane, 2020).
- 51%-84% will be assigned a score of 2, meaning more in than out of the membership set.
- 85%-100% will be assigned a score of 3, meaning fully in the membership set.

Because there are five possible values, this type of fuzzy-set calibration is called five-value fsQCA (Kahwati & Kane, 2020; Mello, 2020). This general calibration pattern of assigning values will be repeated for the two additional outcomes and the causal conditions.

Study Conditions. Based on literature, the program theory, and substantive knowledge of cases, five general causal conditions of interest were identified that could be related to desired outcomes from networking. (See Appendix G for a table of outcomes and their respective indicators.)

For those who blanch at the word "causal" used with such a fundamentally qualitative process, it is worth repeating that "causal" in QCA relates to causal complexity including conjunctural causation, equifinality, and causal asymmetry (Hollstein & Wagemann, 2014; Mello, 2020). QCA can be used to describe a causally complex relationship between condition and outcome sets, but "to allow for *causal attribution*, set theory should be embedded in a theory of causation and a theoretical rationale should be provided as to how the cause brought about its effect (Mello, 2020, p. 69). In other words, "causal" has different meanings depending upon the theory being applied. “Causal” in QCA does not refer to causal inference, nor does it imply causal attribution (Ragin, 2005).

As was true with the outcomes, additional causal conditions exist. For example, according to prior research, land tenure and sustained funding are two conditions of successful community-based resources management (Gruber, 2009). A land tenure system does not exist in Hawaii, however, and cultural norms prevent asking about or sharing information about sustained funding. Although 501(c)(3) nonprofits will have IRS Form 990 on file, groups that are not 501(c)(3) nonprofits will not. Funding data will not be available for all groups, so it was left out of this analysis. Instead, the number of full-time staff members is a proxy indicator for funding. The causal conditions selected were narrowed to these five from a longer list of that included conditions that were not as relevant to the specific context of E Alu Pū and Hawaii.

A maximum of five conditions were selected because of the exponential increase in the number of possible causal configurations with the addition of each condition. With two conditions, for example, a group would either meet set membership criteria for condition 1 only, condition 2 only, or both conditions 1 and 2. With five conditions selected for this study, there are 32 possible configurations of conditions for 36 network member groups. A QCA rule of thumb is to avoid a possible number of configurations that is greater than the number of cases (Kahwati & Kane, 2020).

Fuzzy Set Calibration. As was described for the outcomes, each condition will be comprised of a composite of its indicators. Thus, for each condition, each group will be assigned a single number based on the outcome indicators (see Appendix G). The expectation is that calibration will respond to the data and so may shift during analysis (Hollstein & Wagemann, 2014; Kahwati & Kane, 2020; Mello, 2020; Ragin, 1987). The current thinking about fuzzy set calibration for the conditions are described below.

- Network participation: KUA organizes gatherings, trainings and workshops, and *huakaʻi* (site visits with a purpose) to engage network groups. According to program theory, the longer a group has been a part of E Alu Pū and the more the group has participated in network activities, the more likely the group is to achieve the desired outcomes. Groups with larger participation values will receive higher scores using five-value fsQCA than groups with smaller participation values.
- Connectivity: KUA uses networking as a strategy to help E Alu Pū achieve its desired outcomes, with the hypothesis that greater connectivity will lead to greater outcome achievement. Node-level results from SNA will be combined to assign each group a connectivity value. Groups with larger connectivity values will receive higher scores using five-value fsQCA than groups with smaller connectivity values.
- Other KUA support: In addition to network coordination, KUA provides individualized facilitation and technical assistance to groups who request assistance. Again, the hypothesis is that groups who receive these types of extra support will be more likely to achieve the desired outcomes. Groups who have received a greater degree of KUA support will receive higher scores using five-value fsQCA than groups who have received less KUA support.
- Group stability: It is possible that conditions outside of KUA staff's coordination, facilitation, and support are more important contributors to the successful achievement of desired outcomes. Logically, longevity and stability for a group will play an important role. The indicators (see Appendix G) will be compiled to create a

stability value for each group. Groups with larger stability values will receive higher scores using five-value fsQCA than groups with smaller stability values.

- Outside support: Finally, KUA is not the only organization providing support to community-based resources management in Hawaii, and E Alu Pū is not the only network. Perhaps support a group receives from other partners plays a greater role in its achievement of the desired outcomes. The indicators (see Appendix G) will be compiled to create an outside-support value for each group. Groups with larger outside-support values will receive higher scores using five-value fsQCA than groups with smaller outside-support values.

Calibration is a critically important part of QCA analysis. The idea is not to randomly assign scores based on even distribution of percentages or the average score of the group. "Such approaches miss the fundamental advantage of QCA, namely that *meaningful variation* can be separated from irrelevant variation" (Mello, 2020, p. 119). Good calibration practices include thorough documentation of the decisions made throughout the process, transparency about data sets used, reporting about calibration criteria and thresholds, and directionality should be included in the name of the set (e.g., *stronger* connectivity) (Mello, 2020).

Set Configurations. After all network member groups are assigned scores for each outcome and condition, analysis can proceed using specialized QCA software. For this study, open-source R software with R Studio and specialized QCA packages will be used (Duşa, 2019). To conform to established good practices for using QCA, the analysis first will uncover any conditions identified as "necessary"—or those always present when an outcome occurs (Mello, 2020; Schneider & Wagemann, 2010). Goodness-of-fit for each condition will be assessed using consistency, which is the proportion of configurations made of the same conditions that have resulted in the outcome (Mello, 2020). Mello (2020) recommended a threshold of .90 for consistency to accept the condition as “necessary.”

QCA Result. The next step in the analysis is to create the truth table as described earlier in this chapter. The truth table, the “core of QCA” (Mello, 2020, p. 145), will indicate the fsQCA scores for each outcome and condition for each group so that patterns can be detected. The result of a truth table is a causal pathway that identifies the conditions, whether sufficient or necessary, for the outcome. The purpose, however, is not to merely receive and report the result. Developing the truth table is more of an iterative process like qualitative data analysis, for which the researcher returns to the data to learn more and may alter the analysis based on what is learned. Mello (2020) suggested that a preliminary truth table be constructed during early phases of analysis to provoke deeper thinking about the selection of conditions. Kahwati and Kane (2020) suggested that calibration, conditions, and even case selection could be revisited based on preliminary truth table analysis. This approach is not unique to QCA but is common to qualitative research and mixed methods: “The cases evolve throughout the study. This philosophy holds that many perspectives are available and that they need to emerge during the research process to fully describe the complexity of the case” (Creswell & Plano Clark, 2018, p. 117). QCA, as a case-oriented method, and mixed methods case study both utilize an evolutionary process of analysis.

All revisions, these authors counseled, must be made based on substantive and theoretical knowledge rather than using a haphazard approach (Kahwati & Kane, 2020; Mello, 2020). Researchers work with the truth table to arrive at a solution, which is the identification of sufficient conditions and combinations of conditions through an algorithmic process called minimization (Kahwati & Kane, 2020). The solution will identify the necessary, sufficient, and combinations of conditions for the outcomes.

Methodological Integrity for QCA

"Perfect set relations can rarely be found in the social sciences" (Mello, 2020). Still, as researchers have developed QCA, they have established practices that are used to assess the methodological integrity of QCA results. These, which I will employ, include careful documentation of conditions and their treatment throughout the analysis, transparent data sources, raw and calibrated data for other researchers to inspect, R scripts that were produced available for inspection, transparent calibration methods and decisions with reported justification, and use of directional terms for set names (e.g., *engaged* public, *severe* damage).

A primary threat to integrity in QCA research is the temptation to perform the analysis by rote, mechanically following the steps without engaging with the data. Mello (2020) urged researchers to stay true to the "*case-based nature* of QCA" (p. 189). Case selection, conditions selection, calibration—all are rooted in substantial, meaningful case knowledge. Approaching QCA with the idea that data can be plugged in and run through the analysis in hopes that R will spit out meaningful results is paving a road of trouble. The best way to produce credible, meaningful results is to use QCA appropriately.

Study 3: Comparing SNA Alone to SNA with QCA

After mixed methods integration using QCA is complete, the final study remains: to compare results from Study 1 and Study 2 to answer the research question of what QCA can add to an understanding of networking outcomes. I will compare the results of Study 1, the quantitative study using SNA, with the results of Study 2, the case study using QCA. Collective action theory will provide framing for the results, which I will present using the dimensions named by Ostrom (2009) and Crossley and Ibrahim (2012):

- The structure of connectivity between group members
- Whether or not individuals are compelled to participate
- Historical actions
- Face-to-face communication
- The nature of the collective benefit
- Who bears the costs of collective action toward a common benefit
- Personal contribution to a collective benefit
- Number and heterogeneity of individuals
- Trust
- Consciousness-building
- Consensus-building

Based on the comparison of SNA and QCA, I also will report on methodological conclusions using the frame of systems and complexity theory:

- Boundaries, level, and unit of analysis for the system
- Context in which the system exists
- Interrelationships present in the system and distinctiveness of interrelationships
- Motivations, behaviors, values, and feedback effects
- Nonlinear timing

Using the theoretical characteristics listed above, I will present the results in a joint table like those recommended for use with mixed methods studies (Creswell & Plano Clark, 2018) so that results for each study are displayed side by side. In narrative format, I will discuss the results of the studies, identifying what information both studies produced and what unique information was gleaned from each. Based on the comparison, I will elaborate the additional understanding about networking outcomes gained by using QCA with SNA. Finally, I will summarize my own experience from this study to help future evaluators and researchers consider the challenges and benefits of SNA and QCA as they decide how to approach their own network evaluations.

Chapter Three Summary

To answer the research questions about networking outcomes and the contribution of QCA, I will conduct three scaffolded studies. For the first study, I will use a quantitative nonexperimental descriptive design and analyze archival survey data with descriptive statistics, frequencies, and SNA. For the second study, I will employ an explanatory mixed methods case study. I will inductively and then deductively analyze data from interviews, documents, and archival records using constant comparative analysis to uncover the patterns in the data. I then will take the extra steps to integrate the quantitative and qualitative data using QCA, which will require quantization of the qualitative data. For the third study, I will compare the results from Study 1 with results from Study 2 to discuss what QCA contributes to an understanding of networking outcomes.

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APPENDIX A.

Research Matrix

Research questions	Indicators	Data sources	Data collection methods	Data analysis methods
To what degree are various network structures and relationship characteristics present for the E Alu Pū network and member groups?	Relationship and structure measures	KUA	Archival survey data	Social network analysis
To what degree have intended outcomes been achieved by E Alu Pū member groups?	Outcome variables	KUA	Archival survey data	Frequency counts, descriptive statistics
For the E Alu Pū network, what intended and unintended outcomes emerge from networking experiences and activities?	Comments linking networking and outcomes	E Alu Pū, KUA	Interviews, documents, archives	Constant comparative analysis
For the E Alu Pū network, what conditions are necessary and sufficient to achieve the intended outcomes?	Relationship and structure measures, outcome variables, comments linking networking and outcomes	E Alu Pū, KUA	Archival survey data, interviews, documents, archives	Qualitative comparative analysis
How does qualitative data about the E Alu Pū network help to explain or contextualize quantitative survey data about network relationships, structures, and outcomes?	Relationship and structure measures, outcome variables, comments linking networking and outcomes	Qualitative results, quantitative results	Archival survey data, interviews, documents, archives	Integration of QUAN and QUAL results
When compared with using SNA alone, what additional understanding about networking outcomes can be gained by using QCA with SNA?	Results from Study 1 and Study 2	SNA results, QCA results	SNA, QCA	Comparison of SNA results and QCA results

APPENDIX B.

Subunit and Network-Level Moderating and Outcome Variables

Subunit Moderating Variables	Subunit Outcome Variables	Network-Level Moderating Variables	Network-Level Outcome Variables
• Node centrality • Node density • Number of links • Node indegree • Node outdegree • Multi-relational ties • Number of community volunteer hours • Number of years in existence • Number of people on the outreach list • Number of full-time staff • Type of group (nonprofit, fiscally sponsored, informal) • Memberships in networks • Receipt of technical assistance • Created by local community • Partnerships with resource management agencies • Conflict management process	• Percent of desired policy decisions approved • Degree of participation in decision-making processes • Formal agreement for a site • Degree to which a site management plan is used • Degree to which resource law violations are reported • Degree to which environmental observation is practiced • Degree to which environmental restoration is practiced • Degree of perceived site abundance vs. threats • Number of people receiving traditional knowledge instruction • Number of people served • Number of acres stewarded	• Network centrality • Network density • Average number of links per group • Network indegree • Network outdegree	• Percent of network groups participating in decision-making processes • Percent of network groups who responded to calls for help • Percent of desired policy decisions that have been approved

APPENDIX C.

Institutional Review Board Approval for Study

[TO COME ONCE RECEIVED AFTER PROPOSAL DEFENSE.]

APPENDIX D.

Data Collection Logistics Table

Data collection methods	Data sources	From whom will these data be collected	Security or confidentiality	Data quality control
To what degree are various network structures and relationship characteristics present for the E Alu Pū network and member groups?	KUA archival survey data	KUA	• Invitation-only Google Drive • Password-protection	• Pilot-tested • 3 cognitive interviews • 4 reviewers • Cross-checking
To what degree have intended outcomes been achieved by the E Alu Pū network and member groups?	KUA archival survey data	KUA	• Invitation-only Google Drive • Password protection	• Pilot-tested • 3 cognitive interviews • 4 reviewers • Cross-checking
For the E Alu Pū network, what intended and unintended outcomes emerge from networking experiences and activities?	Interviews, KUA archival data and documents	E Alu Pū *po'o,* KUA, Coordinator	• Informed consent • Password protection • Invitation-only G-Drive	• Interview protocol • Cross-checking/ verifying archival data
For the E Alu Pū network, what conditions are necessary and sufficient to achieve the intended outcomes?	Interviews, KUA archival survey data, KUA archival data and documents	E Alu Pū *po'o,* KUA	• Informed consent • Password protection • Invitation-only G-Drive	• Tracking treatment of data and R scripts • Transparent data sources • Directional terms for set names • Rooted in case knowledge
How does qualitative data about the E Alu Pū network help to explain or contextualize quantitative survey data about network relationships, structures, and outcomes?	Study 1 and 2 findings	NA	• Password protection	• Triangulation • Member-checking • Multiple perspectives • Critical friend review
When compared with using SNA alone, what additional understanding about networking outcomes can be gained by using QCA with SNA?	Study 1 and 2 findings	NA	• Password protection	• Triangulation • Member-checking • Multiple perspectives • Critical friend review

APPENDIX E.

Draft Interview Protocol

Introduction: Introduce myself (include connection to KUA) and engage in small talk as necessary to set a friendly, comfortable tone. Explain the current project *("I am conducting interviews to inform to better understand how networking does or does not affect what happens ar your site. I'm interested in your opinions about E Alu Pū.")* Explain the interview process and purpose *("I'm going to be asking you some questions about E Alu Pū, your work with the the network, and your perceptions the activities and any results.")*

1. Can you tell me a little bit about the group you represent in E Alu Pū?
2. When did your group start participating in E Alu Pū?
3. Why do you participate?
4. How consistent has your participation been? Can you say a little about why?
5. Have there been activities, projects, or goals that your group has been able to achieve because of your participation in E Alu Pū?
6. Is there anything that you have achieved in the past 17 years that you think would not have been possible without your participation in E Alu Pū? If so, what?
7. Now thinking beyond your group and about Hawaii in general, has anything been achieved in Hawaii because of E Alu Pū?
8. Overall, are there things E Alu Pū does well that others can't do or don't do?
9. Overall, do you think a network is needed? Why or why not?
10. Is there anything you had hoped E Alu Pū would achieve by now that it has not been able to achieve?
11. Does E Alu Pū have what it needs to accomplish those achievements? (Relationships, resources, etc.) If not, what is missing?
12. [If they have not mentioned it, ask specifically about the shared goals created by E Alu Pū network groups.]
13. Is there anything else you'd like to share about your experiences with E Alu Pū?

INTERVIEWER REFLECTIONS

This is a space to jot down quick notes directly after the interview. What was surprising? What responses are swirling? Why do I think that is?

APPENDIX F.

E Alu Pū Desired Outcomes and Indicators Being Examined

Desired outcome	Site-level indicators	Network-level indicators	Research-based evidence
E Alu Pū groups are decision-makers in resource management in Hawaii.	• % of policy decisions that network groups advocate for at a site level that are approved • Degree of network groups' participation in decision-making processes at the site level	• % of network groups participating in decision-making processes • % of policy decisions that network groups advocate for at a network level that are approved	• Curtis et al. (2014) • Dressler et al. (2010) • Gruber (2010) • Murphree (2009) • Ostrom (2000, 2009) • Sterling et al. (2017)
E Alu Pū groups effectively manage natural and cultural resources at their sites.	• Formal agreement tying a group to site (e.g., MOU) • Degree to which the group: uses a site management plan reports resource law violations practices environmental kilo (observation) practices environmental restoration • Degree of perceived abundance vs. threats at site • # of people for whom the group provided traditional knowledge instruction • # of people the group served through its programs • % of desired acres the group stewards		• Alexander et al. (2018) • Berkes & Ross (2013) • Blythe et al. (2017) • Bodin and Crona (2008) • Dressler et al. (2010) • Ernston (2011) • Gooch & Warburton (2009) • Gruber (2010) • Murphree (2009)
E Alu Pū groups display support and solidarity for one another.	• Degree of response to calls for help at the site level • Centrality of a network member's "trust network"	• % of network groups who responded to kahea (call for help) at network level • "Trust network" density • Network connectivity (centrality, density, average # of links/group, indegree, outdegree)	• Blythe et al. (2017) • Curtis et al. (2014) • Garcia-Amado et al. (2012) • Lozano et al. (2016) • Ostrom (2000, 2009) • Schnegg (2018)

APPENDIX G.

The Causal Conditions and Site-Level Indicators for E Alu Pū

Causal conditions	Site-level indicators
Network participation	• # of years of participation in E Alu Pū • % of trainings/workshops attended • % of gatherings attended • % of huakaʻi (site visits with a purpose) attended
Other KUA support	• Degree (low, medium, high by comparison) of facilitation support by KUA • Degree (low, medium, high by comparison) of TA support by KUA
Connectivity	• SNA node level measures (node centrality, density, number of links, indegree, outdegree, and multi-relational ties)
Group organizational capacity	• # of community volunteer hours • # of consecutive years in existence • Ratio of years in existence to # of leadership transitions • # of people on the group's outreach list • # of FTE staff • Type of group (501c3, fiscally sponsored, informal) • # of additional environmental-related networks they are a part of • # of additional groups providing them TA
Group organizational practices	• Yes/no: Group created by local community • Degree of partnership with resource management agencies • Yes/no: Conflict management

APPENDIX H.

Data Analysis Logistics Table

Data	Data analysis methods	Data products	Data quality
Interviews	• Constant comparative analysis	• Transcripts • Codebook	• Transcript review • Triangulation • Member-checking
Documents, archives	• Constant comparative analysis	• Codebook	• Cross-checking • Member-checking
Archival participation	• Frequency counts	• Data matrix • Tables • Graphs	• Cross-checking
Archival survey	• Frequency counts • Descriptive statistics • Social network analysis	• Data matrix • Tables • Graphs • Network visualization	• Census • Multiple sources
Study 1 findings Study 2 findings	• Qualitative comparative analysis	• Truth table • Necessary and sufficient conditions	• Tracking treatment of data and R scripts • Interview protocol • Transparent data sources • Directional terms for set names • Rooted in case knowledge