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# Exploring the Dynamics of a Long-Term Research Network

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**Abstract**

*Studying the functionality and dynamism of long-term research networks makes it possible to discover underlying collaborative strategies and outcomes, including research productivity. Using a mixed-methods approach, we employed social network analysis (SNA) technique, original network indices, and qualitative interviews to operationalize the network dynamism of an entomology research team by explaining its reconfigurations over time. The study focused on a sub-network composed of researchers and Extension specialists who remained in the network through three successive reconfigurations over seven years. Network indicators revealed an increasingly connected structure for the sub-network after each project reconfiguration, while network indices revealed the dynamism of the overall research network. Dynamism was based upon the movement of team members in and out the network. Team members' movement in and out of the network was motivated primarily by their interest in investigating the same phenomena. We concluded that long-term scientific collaborations are governed by team members' scientific goals and professional desire for productivity, while geographic closeness and friendships were less important variables for continuing collaboration.*

***Keywords**: scientific collaboration; social network; team dynamism*

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## Introduction

The evaluation of long-term scientific research networks requires the use of specific indicators that allows for mapping progress beyond research results that may not be visible in the short term (Olson et al., 2008). Such progress, and also the success of scientific collaborations, is mainly measured at two levels, the individual level of the researchers involved and the level of research productivity. At the individual level, success and progress are traditionally measured by considering social capital, which includes indicators related to one's personal and/or professional status improvement as indicated by their record of productivity evidenced by the curriculum vitae (Contandriopoulos et al., 2016; Porac et al., 2004). In addition, the success and progress of collaborative research has been measured by research products such as discoveries, patents, and published works (Atkinson et al., 1998; Olson et al., 2008).

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However, Olson et al. (2008) exposed the extent to which these traditional approaches may not always be appropriate to evaluate long-term scientific collaborations. They explained that scientific results are generally higher-level objectives of research collaboration and, therefore, other intermediate results are worthy of exploration, such as mapping a researcher's journey towards scientific success through social network analysis (SNA).

The types of indicators for mapping ongoing scientific collaboration outcomes include securing new funding and creating new collaborations. The latter reflects the dynamism of scientific research networks that evolve over time (Defazio et al., 2009; Olson et al., 2008). Indeed, long-term scientific collaborations are either stable or dynamic (Gulati, 1999). The notion of stability suggests that the network continues to function with most of its initial members while a dynamic network evokes the idea of change, whereby new researchers join the network as others exit (Li et al., 2017). A number of studies have explained the mechanisms of stability and dynamism that govern scientific research networks that persist over time (Atkinson et al., 1998; Li et al., 2017; Maggioni et al., 2013).

Scientific collaboration has been extensively studied, mainly through the analysis of researchers' curriculum vita; however, new research tools allow social scientists to study networks using the SNA approach and to examine networks' longitudinal dynamics through quantitative analytic techniques including mathematical models (Barabási et al., 2002; Jeong et al., 2003; Lara-Cabrera et al., 2014; Madaan & Jolad, 2014).

Operationalizing the stability of the network over time beyond mathematical models remains problematic and under studied. Therefore, there is a need to complement quantitative approaches to analyzing the dynamics of research networks with qualitative approaches (Bright et al., 2018; Gulati, 1999; Huggins, 2010). To this end, the research reported here used a mixed-methods approach to provide a greater understanding of the dynamism of a long-term research network by examining qualitatively the determinants underpinning the network's successive reconfigurations.

The results of this study contextualize strategies used to establish collaborative scientific networks in the pursuit of new discovery. This outcome is in line with the American Association for Agricultural Education's (AAAE) Research Priority Area 7: Addressing Complex Problems (Roberts et al., 2016) by informing policy makers about the complex processes inherent in scientific collaborations and providing information to maximize team productivity within federally funded research projects.

## Purpose of the Study

The purpose of the study was to operationalize network dynamism among a land-grant university entomology research and Extension specialists team focused on finding solutions to an invasive berry and cherry pest in the U.S.

To achieve this purpose, we (a) described the dynamism of an entomology research and Extension specialists' network in terms of successive reconfigurations over time; (b) explained the reconfigurations of the long-term network; and (c) described how successive reconfigurations of the network impacted the productivity of the team.

## Literature Review

### Social Network Analysis

SNA is a quantitative approach that allows researchers to examine relationships between and among members of a social system. Borgatti et al. (2018) posited that a social network refers to something active, alive and dynamic and can be quantified by SNA technique, allowing researchers to study how people are connected to each other and to explain relationships within a specified network. Relationships that occur in the social world are empirical social phenomena, whereby SNA offers researchers a particular analytical technique for measuring multiple aspects of the social dynamics that govern networks, including the social structure created by the existing relationship between social entities (Hosseininia et al., 2016; Mead, 2001). Additionally, Bright et al. (2018) suggested that SNA is a "set of analytic techniques used to describe social groups by examining the actors in the groups and the connections between them" (p. 238), thereby, reinforcing the case for employing SNA to study social relationships.

A growing interest has emerged in using SNA to explore and evaluate collaborations within academic research networks. For instance, the SNA approach has been used to provide empirical evidence of the structure of scientific collaboration, its functionality and importance for productivity, and the achievement of research team objectives (Contandriopoulos et al., 2018; Defazio et al., 2009; Kaliva et al., 2015). Marabesi and Kelsey (2020) and Dossou Kpanou et al. (2020) used the SNA approach to better understand network structure among a horticulture research team and an entomology research team to gain insight into causality processes and hidden patterns of collaborative networks. Wu et al. (2021) used SNA to study group interactions within the focus group setting.

The advantage of using SNA to explore scientific collaborations is that it allows for longitudinal studies to discover potential ways and patterns of scientific collaborative work (Olson et al., 2008). In an evaluation context, this approach offers the advantage of emphasizing the contextual dynamism that underlies the project's overall outcomes and impact beyond counting outputs.

### Stable and Dynamic Networks

Network stability and dynamism are important for understanding the evolution of long-term research networks and their subsequent productivity. Stability and dynamism explain the determinants underlying the successive reconfigurations of scientific research networks. Tracy and Abell (1994) distinguished three components of network stability that included the size of the network, changes in network members, and network ratings. The latter relates to rating the support that network members grant each other internally.

Stable networks suggest teams whose members remain tied to each other for a long time without renewal. Li et al. (2017) defined stable networks by referring to the proportion of network members who have long-standing cooperative relationships with others. Their definition of network stability highlights two fundamental elements, the duration of the collaborative relationship between the members of the network, and the proportion of members who remain in the network during this period. Chinowsky et al. (2008) concluded that network stability represented the absence of renewal within the network. Conversely, dynamic networks undergo continuous reconfigurations as people enter and exit teams (Balland et al., 2019; Barabási et al., 2012; Bright et al., 2018; Csermely et al., 2013; Huggins, 2010).

## Implications for Dynamic and Stable Research Networks

Network capital refers to the whole network, whereas social capital refers to individual members within the network (Huggins, 2010). Stable and dynamic research networks affect network capital in terms of knowledge acquisition, transfer and retention. Network capital corresponds to the gains obtained by the research network after investing in relationships. According to Huggins (2010), networks invest in relationships to generate the necessary knowledge that increases their overall research network capital.

Stable networks imply a certain homogeneity of information or knowledge within the network; therefore, stable networks appear advantageous for seeking knowledge convergence. Research networks that maintain stability over time tend to generate increasingly homogeneous knowledge (Li et al., 2017). Beyond supporting the quest of homogeneity, network stability is disadvantageous for teams seeking to diversify their knowledge base and advance scientific achievement (Huggins, 2010). Based on the study of a network of co-authors, Li et al. (2017) concluded that a moderately stable network fostered greater knowledge generation and subsequent productivity.

On the contrary, dynamic networks undergo periodic reconfigurations to become more innovative and heterogeneous in knowledge creation. Huggins (2010) placed a strong emphasis on the reconfiguration of networks by outlining the advantages of a dynamic network environment. In particular, they argued that in the context of businesses, a dynamic environment was more conducive to creating enterprises by allowing for easy access to various resources within the network. Continuously reconfigured research networks have the potential to access greater diversity among members and produce heterogeneous knowledge, leading to greater innovation (Rand et al., 2011).

## Determinants of Network Dynamics

The literature revealed various reasons for reconfiguring research networks, primarily to improve the process of knowledge creation (Bright et al., 2018). Networks evolve through three main movements including exit, fidelity, and arrival. Network leaders open the network to new researchers with significant social capital and expertise in the field of interest because they seek new expertise or to fill a vacancy (Contandriopoulos et al., 2016; Sonnenwald, 2008). Similarly, for newcomers the quest for new challenges motivates their desire to join a successful research team as well as to work on a complex problem and to increase their social capital (Sonnenwald, 2008). Conversely, members exit the research network due to retirement, a new career opportunity, reorientation of research focus, to explore new research relationships, the search for performative links, the need to improve knowledge, and/or to address a compatibility issue with other network members (Atkinson et al., 1998; Bright et al., 2018; Huggins, 2010; Sonnenwald, 2008).

For researchers who remained in the research network, reasons included preferential attachment (Bright et al., 2018) and collaboration readiness (Olson et al., 2008) as scientists discover people with similar agendas and goals. Both variables encompass the alignment of goals and interest, complementarity knowledge, greater productivity of the team, promising outcomes and discoveries, working styles, and enjoy working together having built trust over time. In addition, stable teams experience reliability, greater opportunities for securing funding, prestige, respect, increased publications, personal compatibility and positive mutual feelings (Bright et al., 2018; Hara et al., 2003; Maggioni et al., 2013; Olson et al., 2008; Sonnenwald, 2008). These determinants are useful indicators for qualitatively understanding the factors that explain stability and dynamism of research networks.

## Conceptual Framework

Our study was underpinned by Tuckman's (1965) team development model, which has informed numerous organizational studies of small groups development (Bonebright, 2010; Miller, 2009). Tuckman's model is based on four consecutive stages including forming, storming, norming, and performing. We focused on the stages of storming, norming and performing. Many scholars have argued that Tuckman's model is useful in describing how teams operate and share information within the network to better understand the process of network achievements (Bonebright, 2010).

The storming stage is the most difficult for team building. Tuckman suggested that at this stage internal conflicts, hostilities, and resistances occur as a result of decisions, goal reorientations, and changes in implementation strategies. Team members seek to assert themselves, prove their worth to other members, while also seeking reciprocity (Tuckman, 1965). The often brief and fragile relationships fluctuate, resulting in polarization characterized by the emergence of subgroups, and members may find themselves isolated or poorly connected with other team members (Bonebright, 2010; Largent, 2016).

The norming stage results in greater team cohesion as members accept each other's roles, relationships are established and stabilized, and members focus on the team's common goals. This stage is exciting because the initial storm has passed, whereby new ideas germinate and big decisions are made and implemented to advance the team's goals (Bonebright, 2010; Largent, 2016).

The performing stage suggests a more cohesive team with members working effectively to achieve the team's overall objectives. Most conflicts are healthy and contribute to successful relationships within the network and are resolved considering the group's overall concerns (Cassidy, 2007). These three aspects of Tuckman's model emphasize the internal dynamics of networks, reinforcing the case for using this model to inform social relationships.

Our study examined the dynamics of a research network in terms of factors that explained successive reconfigurations over time. The concepts of stable and dynamic networks as they appeared in the literature describe the evolution of the long-term network. The literature also revealed underlying determinants of successive reconfigurations of research networks and exposed factors motivating researchers to join or leave a research network.

## Methods

We employed a mixed-methods approach (Plano-Clark et al., 2008) to answer the research questions by combining the SNA quantitative techniques of Borgatti et al. (2018) with three original network indices and qualitative interviews.

### Background of the Research Network

A team consisting of land-grant university research faculty and Extension specialists initially formed in 2009 responded to a call for proposals of the United States Department of Agriculture, National Institute of Food and Agriculture (USDA-NIFA) by submitting a project to solve the challenge of mitigating an invasive pest impacting berry and cherry production. The 2009 grant was funded for three years, hereafter referred to as project zero. Project zero was not included in this study because the project was regional in nature. The second USDA-NIFA funded project started in 2015 for three years, hereafter referred to as project one. The team then reconfigured to apply for a third USDA-NIFA project in 2018 for three years, hereafter referred to project two. The team reconfigured once more to apply for a fourth USDA-NIFA funded project in 2021 for five years, hereafter referred to as project three. At each point, team members exited and entered. Their motivations for doing so are part of our inquiry.

**Population and Sample**

Participants included 13 researchers and Extension specialists selected from the project three team (*N* = 37). Some members worked together for over seven years on three USDA-NIFA funded research projects from 2015 to 2021 (excluding project zero). Participants came from 10 universities and one federal institution. The selected participants of the study included land-grant university research faculty and Extension specialist, post-doctoral research associates, and laboratory technicians. The selection criterion for 11 of the 13 members were those who belonged to the entomology network from project one to project three 2015-21 (*n* = 8) and participants who remained in the network from project two to project three (*n* = 3). These 11 members participated in the survey and were considered in the network analysis portion of this study. The data set also included interviews from two participants (*n* = 2) who exited the network after project two to better understand this phenomenon. The rational for participant selection was to gather information from a variety of team members with different experiences: having remained with the team since project one , having newly joined the team, and having exited the team after project two.

**Mixed Methods Design**

The study was conducted through a sequential explanatory mixed-method design (Plano-Clark et al., 2008). Data were gathered from secondary quantitative data, and qualitative interviews (primary data). The secondary quantitative data were used to compute the network indices, to determine primary links between the participants, to guide the literature review and to design the quantitative and qualitative instruments for investigation. The second step of the mixed method design helped to collect primary quantitative data and to conduct interviews to further explore the research questions. The qualitative and quantitative data were integrated at the interpretation phase of the study. We employed the qualitative data to better explain and support the findings from the SNA analysis.

**Social Network Analysis Technique**

The SNA technique offers a wide range of metrics useful for examining the structure of networks including stable and dynamic collaboration (Borgatti et al., 2018). While numerous research approaches are applied to investigate scientific collaborations (Sonnenwald, 2008), an effective method to capture the dynamic characteristics of the entomology team was to analyze the patterns of ties linking its members over time (Wellman, 1983).

Because our study focused on a team that evolved over seven years, a comparative approach of different metrics was appropriate to identify and evaluate changes in the network structure. First, we designed and compared the different sociograms of the network in regard to its evolution at three points in time based upon the movement of members in and out of the network. Second, we compared a variety of statistical properties of the networks including (a) the number of ties; (b) the density; (c) the average degree; (d) the degree centralization; (e) the dyad reciprocity; (f) the average distance; and (g) the number of components (Borgatti et al., 2018). These specific statistical properties are SNA indicators and their definition and further explanations can be found in Borgatti et al., (2018). We compared these metrics considering the members who remained in the research network over time.

**Network Indices**

To determine the status (dynamic vs. stable) of the network over time, we employed three original indices (a) network retention index; (b) network renewal index; and (c) the global renewal index.

The *network retention index* assessed the level of retention within the network, and subsequently stability. We determined this index using the following formula: number of retained members at the period P + 1 of the project divided by the total number of the network members at the period P of the project times 100. We determined the number of retained members using the following formula: total number of members of the network at the beginning of a given period P of the project minus the total number of members leaving the network at the end that given period P of the project.

The *network renewal index* measured renewal tendency and indicated dynamism within the network and its ability to renew its membership composition by recruiting new members. We determined this index using the following formula: the total number of new members at the beginning of the project at a given period P divided by the total number of members of the network at the beginning of the project at that given period P times 100.

The *global renewal index* measured the overall network's tendency to renew its membership composition. While the network renewal index referred to a given period of the evolution of the network, the global renewal index included all renewals over time by counting new members at the beginning of each period. To calculate this index, we used the following formula: the sum of the number of new members at the end of each period P of the project divided by the sum of the total number of the network members from period P + 1 to the last period P + n of the project times 100.

**Data Collection**

We developed an original questionnaire for the SNA survey and an interview protocol for qualitative data gathering. The SNA questionnaire emphasized (a) team members' acquaintance prior to joining the network; (b) collaboration patterns through co-authorship; and (c) variables influencing retention in the team over time. The survey was administered through Qualtrics®. The participants were informed of the study during monthly team meetings and were formally invited to participate via email with the survey link embedded. Informed consent was obtained prior to completing the survey and interviews. Three follow-up emails were sent to non-responders to encourage survey completion (Dillman et al., 2008). Ten participants completed the self-administered survey for a 91% response rate.

Adopting a pragmatic stance (Morgan, 2014), we conducted semi-structured interviews using Zoom® with a subset of five participants and two participants who exited the network after project two to triangulate the survey data. The interview protocol focused on participants' motivations, barriers, and professional outcomes as a result of collaboration. We also collected archival data regarding the project achievements as part of the summative evaluation process.

**Data Analysis**

Survey data were cleaned by removing missing records and keeping non-respondents in the data set who were referred to by other respondents as prescribed by Borgatti et al. (2018). This option ensured the completeness of the data set and improved the accuracy of the network analysis. Further, we searched Google Scholar citations to triangulate information about co-authorship of published research articles. Researchers' names were also triangulated throughout the three different projects (2015-2021) to determine the number of exits and entrances. Finally, data were pulled from a previous

SNA study by Dossou Kpanou et al. (2020) for data completeness. All of the names were changed to alpha numeric codes (R1) to ensure their privacy.

The cleaned data were formatted in accordance with UCINET 6 software specificities (Borgatti et al., 2002). Data were uploaded to UCINET 6 software and sociograms were generated (Figures 1, 2, and 3). The SNA indicators (Table 1) were computed. Next, network indices were computed using Excel software (Table 2). IBM SPSS version 26.0 was used to perform Kendall's non-parametric statistic test for concordance among raters.

The qualitative interview data were recorded via Zoom® and transcribed using Otter.ai (Lang, 2020). Interview transcripts were cleaned and then stored, managed, and analyzed through ATLAS.ti 9 for Windows (Friese, 2019). The coding process began with creating a code book to identify reasons for entering and exiting the team(s). Significant quotations related to collaboration resulted in four group codes, eleven codes, and nineteen sub-codes. We deductively performed line-by-line coding followed by inductive coding to develop concepts germane to the research questions (Linneberg & Korsgaard, 2019). We used the qualitative data set to triangulate the SNA quantitative data and the network indices. The complete data set allowed us to elucidate the social dynamics of the research network.

Credibility was established through peer debriefing among the research team, including members of the network, and by sharing a manuscript draft with the network to members check the results. Transferability was established through participants selection criteria and thick descriptions of the study context and use of participant quotes. Participants were guided through informed consent and their rights as human subjects prior to participation. Findings were triangulated with multiple forms of data (Lincoln & Guba, 1985).

## Findings

### Description of the Dynamism of the Entomology Network

We found a sub-network of researchers and Extension specialists who constituted the central nucleus of the whole network dynamic. We examined the following variables respectively: participants' professional acquaintances prior to project two, information sharing among the team during project two, and co-authorship of publications during project two. The sub-network structure during project two was captured through the variables of information sharing between researchers (Figure 2) and co-authorship (Figure 3), which revealed a visually more connected network structure when compared to the structure prior to joining project two (Figure 1). These findings suggest that the structure of the sub-network of the team became more connected over time, as would be expected during Tuckman's (1965) norming and preforming stages of team dynamics.

**Figure 1**

*Sociogram of the Team's Professional Acquaintances Prior to Joining Project Two*

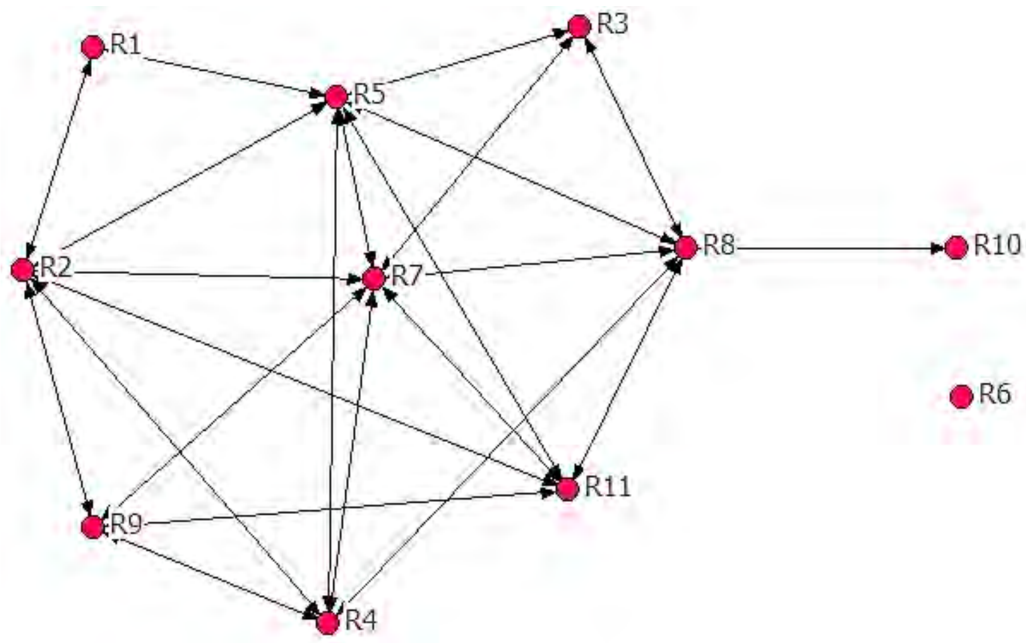



**Figure 2**

*Sociogram of the Team's Professional Acquaintances During Project Two*

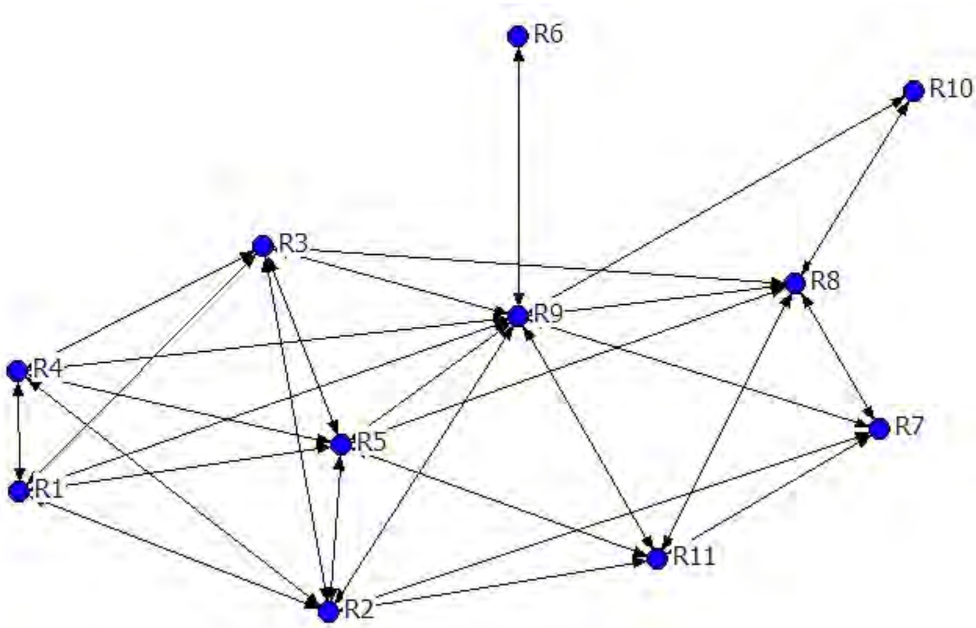


**Figure 3**

*Sociogram of the Team's Co-Authorship During Project Three*

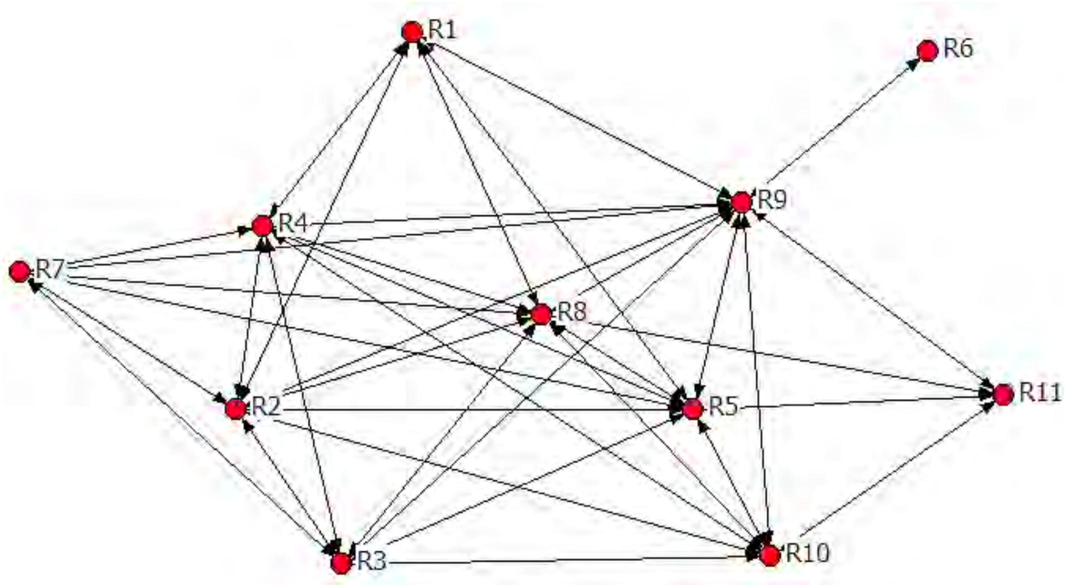



Table 1 compares network indicators characterizing the sub-network structure over time. Data revealed an increasing tendency toward a greater number of ties, density, and average degree over the three projects. The data supports the evolving pattern of the sub-network structure as time passed. In addition, the reduction of the average distance and the decrease in the number of components indicates that team members grew closer to each other, supporting the finding that the structure of the sub-network of researchers became more connected over time.

**Table 1**

*Comparison of Network Indicators Across Time*

| Network Indicators | Project 1 2015 | Project 2 2018 | At the time of the study 2021 | Status |
|---|---|---|---|---|
| No. Nodes | 11 | 11 | 11 | - |
| No. of ties | 46 | 57 | 74 | Increased |
| Density | 0.42 | 0.52 | 0.67 | Increased |
| Avg. Degree | 4.18 | 5.18 | 6.73 | Increased |
| Deg. Centralization | 0.34 | 0.58 | 0.40 | Reduced |
| Dyad Reciprocity | 1 | 0.96 | 1 | Stable |
| Avg. Distance | 1.56 | 1.48 | 1.33 | Reduced |
| Components | 2 | 1 | 1 | Decreased |

**Reconfigurations of the Network Over time**

The three network indices confirmed the dynamism of the research network over the course of three research projects (2015-2021). The number of team members, primarily the principal investigators and co-principal investigators, changed from project to project. However, the total number of members for the three projects was similar (Table 2) while the global renewal index of 59% demonstrated that the network exhibited a high degree of dynamism with significant reconfigurations between projects. The retention index of 33% from project one to project two and of 50% from project two to project three supports the dynamic pattern of the network. Table 2 displays more detail about the indexes.

**Table 2**

*Comparison of Network Indices Over Time*

| Rubrics/Indexes | Project 1 2015 | Project 2 2018 | Project 3 2021 |
|---|---|---|---|
| Number of team members | 18 | 16 | 18 |
| Number of outgoing members | 12 | 8 | |
| Number of incoming members | | 10 | 10 |
| Number of retained members | | 6 | 8 |
| Retention Index | | 33% | 50% |
| Renewal Index | | 63% | 56% |

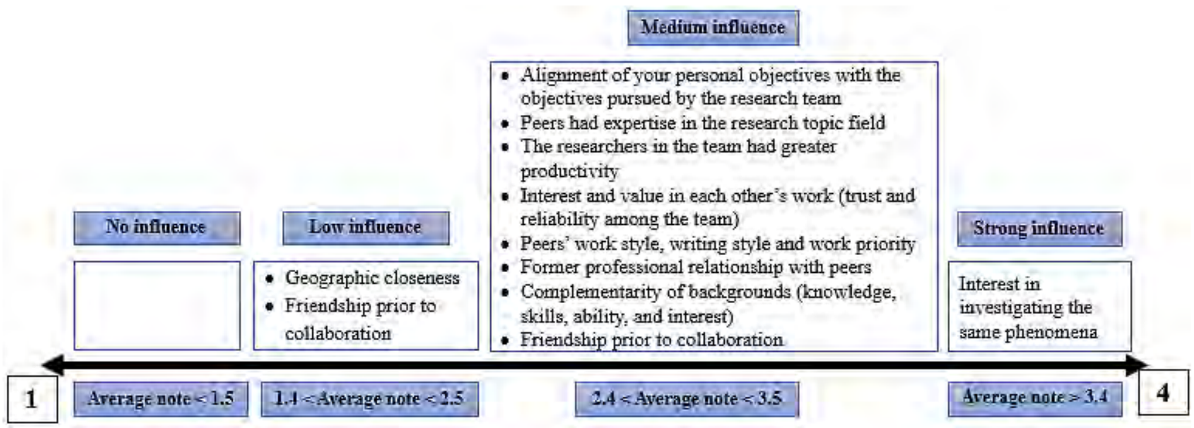
The indices indicate significant departures and arrivals of members in the network from one project to the next over the seven-year time frame. These findings address our first research question concerning the description of the dynamism of the research team in terms of successive reconfigurations over time.

**Successive Reconfigurations of the Network and Its Impact on Project Objectives**

We asked participants to indicate their motivation for participating in the network during the survey. The data were analyzed with frequency statistics on a four-point Likert-type scale ranging from *no influence* to *strong influence*. We computed a weighted average score and discovered that interest in investigating the fruit pest was the most important variable to explain collaboration and retention in the network. Figure 4 details the findings and lists classified factors that influenced retention within the network over time.

**Figure 4**

*Classification Scale of Factors Influencing Team Members' Motivation for Remaining in the Network*




Average scores ranged from 2.5 to 3.4 out of 4 for eight of the eleven factors related to retention in the network (Figure 4). This trend confirms the finding that team members' decision to remain in the network was a multi-factored decision. Kendall's coefficient of concordance of 0.4 ($N = 9$, Chi-Square = 36.03, Degree of freedom = 10, and $p$-value = 0.000 <0.05) attested a medium concordance among the respondents' ratings in terms of factors that influenced retention in the network over time.

Qualitative insights provided a more nuanced understanding to this finding. Team members who participated in the interviews emphasized that project goal alignment best explained the dynamic pattern of the network. They argued that the project objectives, the interests and needs of their stakeholders, and their own research priorities were the primary factors that explained remaining in the network. R2 said,

> I would not leave a project because one person is not being productive. I would continue in that project, but I would just not work with that person as much as I could have because the project goals were my priority. If something is my priority, I am going to look for the people that I can collaborate with. T [pest] is my priority right now, so I am not going to leave any group that is working on this, I mean just awful unless they kick me out. And I doubt that they are going to kick me out, so I am going to stick with that group.

Researchers also postulated that working on a complex problem was one of their personal goals. Indeed, most of the interviewees indicated that the complex nature of the research subject motivated them to continue collaborating with the network to improve the control of the pest, which causes considerable social and economic damage to the berry and cherry industry globally. This finding is consistent with the position of research interest as the major factor influencing collaboration and consequently the network dynamic (Figure 4).

We also found through the qualitative data that desire to access specific expertise and respond to their stakeholders' needs contributed to the significant reconfiguration of the network over time. R9 said,

> I think new people joined [the network] because we needed some horticultural expertise and we got feedback on that from our stakeholders. And so, we added a couple of horticulturists, one in the western U.S. and one in the eastern U.S. Those are the main things I think about in terms of how that team has changed over time [responding to stakeholder needs].

According to the interviewees, the network underwent continuous reconfigurations because of a shift in their approach to implementing the project activities. They explained that the shift in approach aimed to increase the likelihood of achieving the project's expected outcomes. They reported that the shift primarily included an emphasis on aeras with significant acreage of fruit production; therefore, team members from states with small-scale production were dropped from subsequent funding requests. Next, they reported a focus on novel approaches so that team members working on aspects of control that were already known were dropped because their area of expertise would not help achieve the evolving research objectives. As R5 said, "I think over time, the network changed, primarily because of the scale of production in some places, but also the changes in the research priorities and sometimes it just did not meet people's interest." In addition, some team members justified the dynamics of the network by changes in the careers of some members who had transitioned to administrative responsibilities, requiring them to leave the network. These findings explain both exit and entrance movements that govern the dynamic of the network and are consistent with the network indices findings (Table 2).

Continual USDA-NIFA funding undeniably influenced team members' motivation to remain in the network. On one hand, interviewees noted that unless they received funding, they would be less likely to collaborate in this network. On the other hand, others explained that the option to include researchers from regions with large-scale fruit production had created a budgetary constraint leading to the ejection of members from small-scale fruit production regions from the network. That explanation supported the significant movement of researchers entering and leaving between projects two and three as the network indices revealed (Table 2).

## Conclusions, Discussion, and Recommendations

The purpose of the study was to operationalize network dynamism among a land-grant university entomology research and Extension specialist team focused on finding solutions to an invasive berry and cherry pest in the U.S. We added a qualitative dimension to the quantitative SNA indicators and original network indices to enrich the existing literature in terms of explaining the reconfigurations of long-term research networks (aka dynamism).

The SNA indicators and the network indices demonstrated that the network was indeed dynamic with successive reconfigurations. We found that the central nucleus of the research network, which consisted mainly of members who had remained in the network since project one, derived a tightly connected network structure over time. This finding is consistent with Olson et al. (2008), who reported the existence of collaborative patterns behind long-term scientific collaboration networks. Further, based on the interviews with some of the members, we found that time had fostered preferential attachment (Bright et al., 2018) and a collaboration readiness had developed over time because the researchers became more accustomed to each other in addition to sharing similar research agendas and goals (Olson et al., 2008).

The network reconfigurations were governed by the conjunction of several factors (see Figure 4). First, the reconfiguration relied primarily on the objectives of the funded projects. While goal alignment constituted the main factor that fostered the formation of the network and maintained its dynamic pattern since 2015, members exited the team due to non-alignment of their personal objectives. Indeed, with a multidisciplinary, multi-state and multi-institutional network, needs and interests diverged over time despite common objectives between the three projects.

Huggins (2010) noted that by investing in relationships, members generate the knowledge necessary to increase overall network capital, thereby increasing individual social capital. We also found that the team member's overall scientific interests coupled with their stakeholders' interests outweighed personal social capital in regard to team retention. Members were accountable to growers as influential stakeholders. This finding is consistent with other studies that emphasized goal compatibility as one of the determinants influencing network dynamism (Atkinson et al., 1998; Bright et al., 2018; Sonnenwald, 2008).

We established that the team was continually reconfiguring because it was going through the storming and norming stages of Tuckman's (1965) team development model. We discovered that some changes occurred including the reorientation of project priorities and implementation strategies from project two to three. For instance, between the second and third projects, the research emphasis had changed from organic to conventional growing methods, therefore, the PI's decided to include researchers from regions with large scale berry and cherry production to onboard new expertise and to fill a vacancy incurred by expertise needs and promotions. This finding is consistent with Contandriopoulos et al. (2016) and Sonnenwald (2008). Moreover, although the availability of funding remained one of the key drivers of collaboration among researchers, we found that it also contributed to dynamism as a lack of resources led to some network members exiting the team.

At the time of this study, we witnessed a team in full performance mode evidenced by major research decisions taken and implementing novel research protocols, monthly team and sub-team meetings to develop protocols for delivering research results to growers, implementing new ideas for the emergence of team engagement in multi-site experimentation, and prolific publication of research results. All these elements suggest that the team is advancing from Tuckman's norming phase to the performing phase of team development, which is favorable to the achievement of project objectives (Bonebright, 2010; Largent, 2016). Therefore, as Huggins (2010) and Rand et al. (2011) suggested, we postulate that the observed dynamic of the network will achieve more innovative and heterogeneous knowledge generation to satisfy the project objectives.

Evaluations are better understood when they are contextualized. Therefore, we recommend that evaluation teams working on long-term projects place particular emphasis on the dynamic underpinnings the project teams. Indeed, after studying the dynamics of the research network, we were able, as evaluators, to discover some imperceptible foundations of the collaboration pattern and understand the dynamics that underlie the implementation of the project activities (Miller, 2009).

## Limitations of the Study

The study was limited by some of our design choices. We did not consider project zero in our data collection strategy because project zero was regional versus the other three projects, which were national in scope. Given that some members of project zero remained in the network until project three (from 2009 to 2021), consideration of the data from project zero could have affected our conclusions. Also, some members left the team at the end of the project zero and returned to the network during project two, skipping project one. Taking these aspects into account could have influenced our network indices because these members were not new to the team. However, we chose to consider them as new members, thereby reducing their influence on the network indices and our understanding of member exit and entrance.

We compared three different aspects of the network, namely information sharing between researchers (Figure 2), co-authorship (Figure 3), and acquaintance before project two (Figure 1) to conclude a more connected network structure over time. The option of comparing three different aspects of the network did not influence our conclusions. Indeed, for the studied sub-network, acquaintances had evolved, exchanges between researchers had intensified, and the number of co-authored publications had increased. Finally, although the results of this mixed-methods study are not generalizable, our novel methods and study design offers a window of opportunity to other researchers seeking to explore long-term collaboration networks.

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