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An exploratory study of STEM teachers' mentorship networks

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Abstract

Background: The Noyce Scholarship Program was created to attract and retain science, technology, engineering, and mathematics (STEM) teachers in high-need schools. Teacher support networks, and specifically mentorship support, have been linked to increased retention of high-quality teachers in the classroom. Using a sample of Noyce teachers, we used a multilevel model to explore how the characteristics and composition of novice teachers' support networks are related to the likelihood that they receive mentorship support, and further, how characteristics common among Noyce programs are related to mentorship support.

Results: Findings suggest that the characteristics and composition of a teacher's network, as well as certain Noyce program characteristics, contribute to the likelihood that teachers receive mentorship support from their larger support network.

Implications: The results of this study highlight the importance of considering how the design of teacher preparation programs may contribute to continued mentorship support for early career teachers, and ultimately, their retention in the classroom.

Keywords: Novice STEM teachers, Support networks, Mentoring

Introduction

For decades, the American education system has struggled with the costly and persistent challenge of adequately staffing schools with qualified teachers (Carver-Thomas & Darling-Hammond, 2019; Darling-Hammond, 1984, 1997; Goldring et al., 2014; Ingersoll et al., 2021; Milanowski & Odden, 2007). Efforts to alleviate this problem focus on both recruitment and retention, though staffing shortages can be primarily attributed to the challenge of retaining high-quality teachers (Ingersoll, 2001). University-based teacher education programs, federal government, states, and districts invest in interventions to prepare and retain competent and committed teachers for long-term careers in the classroom (Podolsky et al., 2016). The National Science Foundation's (NSF) Robert Noyce Teacher Scholarship Program (Noyce program) was initially funded to increase the number of highly qualified teachers working in high-need schools. The overall purpose of the Noyce program is to recruit individuals with strong academic backgrounds in science, technology, engineering, and mathematics (STEM) as teachers to work in high-need schools and to continue to support them as early career teachers. This is crucial, as graduation requirements have changed over the past few decades, resulting in an increase of students enrolling in STEM coursework, and thus an increased demand for qualified STEM teachers (Ingersoll et al., 2021). Schools serving academically disadvantaged students often experience difficulties retaining teachers, especially early career teachers (Hanushek et al., 2004) and math and science teachers (Carver-Thomas & Darling-Hammond, 2019). Noyce programs intend to help solve this problem by developing effective STEM teachers capable of adjusting to difficult settings in high-need schools. Though definitions of effectiveness vary and remain a controversial

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issue, teacher effectiveness is generally defined as a teacher's ability to utilize approaches, engage teaching strategies, and make connections to students leading to positive student outcomes (Job, 2017; Stronge et al., 2011). Individual Noyce programs, located in universities throughout the United States, provide various types of support to participating scholars, such as induction programs, networking opportunities, and mentoring in order to help new teachers manage the challenges of the profession. However, no research project has investigated the impact of Noyce programs on teachers' support networks and retention at the national level.

In 2016, NSF funded a research project to explore the role of teachers' social networks and self-efficacy in the retention of Noyce teachers. The purpose of this exploratory study was to understand the composition and structure of early career teachers' support networks. In their systematic review of the literature, Vangrieken and colleagues (2015) found that teachers' collaborative networks affect teacher effectiveness and retention, such that teachers with strong networks are more likely to teach effectively and to remain in high-need schools. Through collaborative support networks, teachers can develop social capital, which is related to teacher learning, job satisfaction, and retention (for review, see Demir, 2021). However, the relationship among teacher support networks, Noyce program characteristics, and retention has never been explored within the context of the Noyce program. Using a subset of data collected as a part of the larger exploratory study, this study explores how teachers' support network composition, Noyce program experiences, and length of time teaching are related to the mentorship support teachers receive from their social support network.

Literature review

Investigations into why teachers leave the teaching profession reveal complex motivations, including teachers' personal characteristics, such as age and years of experience, and school characteristics, such as the demographics of the student body and resource allocation (Borman & Dowling, 2008; Carver-Thomas & Darling-Hammond, 2019). Teachers' perceptions of their school environment are also important for understanding their intent to continue teaching (Djonko-Moore, 2016; Sedivy-Benton & Boden McGill, 2012). Teachers commonly cite job dissatisfaction, and dissatisfaction with school administration, in particular, as a primary reason for leaving the teaching profession (Carver-Thomas & Darling-Hammond, 2017; Ingersoll, 2003; Struyven & Vanthournout, 2014). Conversely, teachers are more likely to report intentions to remain in the classroom if they perceive their workplace to be supportive, feel a sense of control in their schools and their classrooms, and perceive that they have a high degree of influence within their schools (Sedivy-Benton & Boden McGill, 2012).

Retention among novice teachers: a social network perspective

The early years of one's teaching career are especially important with regard to retention, with around 30% of teachers leaving the teaching profession within the first 3 years of teaching (Ingersoll, 2003) and 40% leaving within 5 years (Ingersoll et al., 2021). Thus, novice teachers (those with three or fewer years of teaching experience) warrant special attention in addressing teacher retention. One mechanism for investigating novice teacher retention is social network analysis (SNA), in which the quantity and quality of teachers' connections, or variations in teachers' social capital, are used to explore teachers' decisions to continue teaching (Baker-Doyle, 2010). For example, researchers have used SNA to study the relationship between novice teachers' social networks and support, a crucial factor associated with teacher retention (Baker-Doyle, 2012; Thomas et al., 2019). A study of the networks of 24 first-year teachers revealed nuances in the types of support teachers receive from those within and outside their schools (Baker-Doyle, 2012). Findings showed that teachers received support from other professionals, often other teachers at their schools, who helped problem-solve, collaborate, and understand school norms and practices. Novice teachers with a close, homogenous support network were more confident in their understanding of the school environment and felt they had more social capital within their school. Novice teachers' networks also reflected support received from individuals who were not teachers themselves, but supported teachers' growth by providing different philosophies on the field of education and helping teachers engage with curriculum in different ways. These networks were more diverse, with teachers seeking support from those with varied backgrounds and experiences, such as students or school volunteers. When novice teachers leveraged this support network, they adjusted their teaching practices as a result by including, for instance, student perspectives in their curriculum (Baker-Doyle, 2012). In a social network study of novice teachers in Belgium, Thomas and colleagues (2019) found that participants received support from six colleagues, on average, each week. However, the frequency of this support was not significantly related to participants' job satisfaction or intrinsic motivation to teach, both of which are key factors in retention. Rather, the size and perceived usefulness of a teacher's network were positively related to job satisfaction and teachers' intrinsic motivation to teach (Thomas et al., 2019). Scholars have also used SNA to explore the characteristics of those providing support to novice teachers and the influence of these individuals on the experiences of novice teachers. For example, burnout levels among novice teachers at the end of the school year are related to the level of burnout among the mentors and colleagues within their social network (Kim et al., 2017). Given the association between teacher retention and teachers' perceptions of workplace support, these findings have implications for understanding the type of support that is most useful for novice teachers and the characteristics of those who provide this support, potentially impacting novice teachers' decisions to remain in the field.

The importance of mentorship for novice teachers

Induction programs are commonly used to support teachers as they transition from roles as preservice teachers to novice teachers. These programs differ in content, format, and requirements, but many involve mentorship for novice teachers, to the extent that scholars often use "induction" and "mentoring" interchangeably when discussing the initial years of teaching (Long et al., 2012). Induction and mentorship can positively influence teachers' commitment and retention (Ingersoll & Kralik, 2004; Ingersoll & Strong, 2011; Smith & Ingersoll, 2004). Across multiple studies, novice teachers, including Noyce program participants, have described mentoring as an important and helpful component of the induction programs they participated in (D'Amico et al., 2020; Huling et al., 2012; Hutchison, 2012). These anecdotal reports are supported by data showing that induction programs that emphasize mentorship can improve teacher retention. For example, in a study of novice teachers who received weekly visits from a mentor, participants' 5-year retention rates exceeded that of their state and local region (Huling et al., 2012). Similarly, in a nationally representative sample of first-year teachers, participants with a mentor in the same discipline were less likely to switch schools or leave the teaching profession after their first year (Smith & Ingersoll, 2004). Studies of participants in the Noyce program reveal similar findings, with retention rates of 90% or higher during the first 3 years of teaching (D'Amico et al., 2020; Oliver, 2015). These findings, while promising, are based on small samples of Noyce scholars and further research is needed to understand how, specifically, mentoring contributes to high teacher retention rates within Noyce scholars.

The literature described above demonstrates that mentorship is a crucial form of support for novice teachers. However, social network studies have found that the relationship between retention, support, and mentorship is nuanced, with the structure of one's network and the characteristics of individual mentors influencing the experiences of novice teachers. Not all induction programs are equivalent, and mentorship can look vastly different across these programs (Long et al., 2012). Long and colleagues call for further research on how mentoring takes place in induction programs and how novice teachers incorporate themselves into the existing school community (2012). In order to better understand the ways in which mentorship and support influence novice teacher retention, additional research is needed on effective mentor support and how novice teachers' support networks change and evolve compared to networks of more experienced teachers. Therefore, it is important to understand who provides mentorship to teachers at different stages of their career, and further, how the composition of teachers' social networks is related to the types of support that they receive.

Theoretical framework

In this study, we use SNA as the process for investigating social structures through the use of network and graph theories, allowing for the exploration of patterns of social ties among network actors, such as teachers (Bidart et al., 2020; de Nooy et al., 2005). Network theory assesses outcomes by examining the relationships between actors, rather than based on variables associated with actors themselves, as is common in traditional social science methodologies (Borgatti & Ofem, 2010). SNA assumes that these relationships, or social ties, between or among people matter because they transfer behavior, attitudes, information, or goods (de Nooy et al., 2005; Wasserman & Faust, 1994). In the case of this study, we explore the transfer of support via mentorship or coaching from people in a teacher's network to the teachers themselves. SNA combines quantitative and graphical data to provide a more complete and rigorous analysis of these social relationships (Borgatti & Ofem, 2010). The resulting map of relationships, known as a network, is defined as "a set of nodes or actors, along with a set of ties of a single type that connect the nodes" (Borgatti & Ofem, 2010, p. 19).

One way to examine networks is to take an ego-centric or personal network approach (Borgatti et al., 2009). Using this approach, a teacher's network is examined from their own perspective of their network and its structure. One advantage of the personal network approach is that the participant is not limited to a predetermined network, which is especially important if the whole network is not known or may not even exist (Carmichael et al., 2006). For instance, in education, teachers often go to other teachers in their school for advice on one aspect of their job, but may reach out to teachers outside their school for advice on other aspects. A personal network approach allows the researcher to examine network connections across institutional or even geographic boundaries and does not artificially try to bound a network by researchers' predeterminations. Additionally, a personal network approach allows the teachers to define their own support networks and the connections that exist within those networks. For example, two teachers from the same school may have very different types of people that they rely on for mentorship support from within or outside of their school. Further, researchers can examine different aspects of the connections within a teacher's personal network to capture variations across their support networks, such as the number of other people in the network, frequency of connections, depth of connections, quality or value of connections, or expertise of connections (Baker-Doyle, 2010; Carmichael et al., 2006; Coburn et al., 2012). By exploring mentorship support via social network theory, one can then examine the differences in teacher networks to understand how those differences impact the support received.

The current study

This study is situated within a larger exploratory study that examines the relationships that may exist between Noyce teachers' support networks, self-efficacy, and retention (for more information on this study see, Alemdar et al., 2022; Gale et al., 2021). While the larger study focused more broadly on these topics, this paper will focus specifically on teachers' mentorship support networks, guided by the following two research questions: (1) how does the composition of novice Noyce teachers' mentorship support networks compare to those of more experienced Noyce teachers? and (2) what is the relationship between Noyce program characteristics and receiving mentorship support from a teacher's support network?

Research design and method

Participants

All teacher participants in this study participated in the Noyce program. To recruit participants, we compiled a database of Noyce programs and contacted each program, inviting them to forward information about the study to teachers who had completed their program within the last 5 years. Teachers representing 47 Noyce programs across 30 states within the United States took the survey. We removed from the data set any teacher who responded to the survey and identified only one other person in their network, as is recommended for studies of personal networks (Perry et al., 2018). Thus, the final sample in this study included 165 teacher respondents, hereby referred to as "egos", who identified a total of 1182 individuals in their support network, hereby referred to as "alters". The network size (number of people in their support network) of the 165 egos ranged from two to 20, with an average of 7.16 alters across the 165 independent personal networks. One-hundred-three egos indicated that they have taught for 4 or more years, and are hereby referred to as "experienced teachers". The remaining 62 teachers indicated that they have taught for 3 years or less, and are hereby referred to as "novice teachers". All participating teachers taught STEM courses, the majority of whom taught science. Table 1 provides the demographics of egos (i.e., teachers), as well as the perceived demographics of their alters.

Survey instrument

Here, we describe a comprehensive survey, referred to as the Teacher Personal Network Survey (TPNS), developed within the context of a much larger research program to collect information on teachers' personal support networks. More specifically, the survey assessed characteristics of participants' ties to members of their support network (e.g., strength of ties, relationship of alters to ego, type of support provided), alter demographic

Table 1 Demographics of teacher participants and the perceived demographics of their alters

Demographic variable	*n*	%
Ego demographics		
Gender		
Female	117	70.9
Male	48	29.1
Race		
White (non-Hispanic)	125	76.7
Black/African American	11	6.7
Latino/a	11	6.7
Asian American or Pacific Islander	7	4.3
Other	2	1.2
Multiple races	7	4.3
Grade level taught		
Middle school	53	32.5
High school	110	57.3
Alter demographics		
Gender		
Female	751	64.0
Male	423	36.0
Race		
White (non-Hispanic)	940	82.2
Black/African American	105	9.2
Latino/a	46	4.0
Asian American or Pacific Islander	20	1.7
American Indian/Alaska Native/Native Hawaiian	2	0.2
Other	14	1.2
Multiple races	17	1.5

information (e.g., alter gender), and ties among alters. Additionally, the TPNS gathered information on respondents' demographics, school climate, self-efficacy, and likelihood of retention.

Survey development

We developed the TPNS survey instrument using an exploratory sequential study design in which we used qualitative methods to inform the primarily quantitative TPNS, and the TPNS was further validated with additional qualitative methods (Creswell & Plano Clark, 2007). In the first qualitative stage of survey development, we developed an interview protocol to elicit information from former Noyce scholars (i.e., current teachers) regarding their support networks. Members of the research team conducted the interviews with 10 teachers, with each interview lasting about 45 min, on average. Interviewers asked teachers about their experiences and perceptions around five constructs, including their sources of self-efficacy (Morris & Usher, 2011), school characteristics, their support network, and their experiences in the Noyce program. With regard to their support network, the interviewers gathered information from participants regarding the types of people who provide them with support, if those people know each other, in what ways support is provided to them, and the types of support that they receive as a teacher. For example, interviewers asked, "what types of support have you received since you began teaching?" and "tell me more about the people who have provided you the support that you've described." We then summarized interview data across teachers for each section of the protocol and subsequently used these summaries to inform the initial development of survey items. Interview data proved particularly useful for refining the response options for several survey items, such as the types of support teachers reported receiving, the ways in which teachers knew people within their networks, and the characteristics of teachers' Noyce programs.

In the second stage of instrument development, we piloted a draft version of the TPNS survey with 22 teachers. The development of pilot survey items was guided by the results of the first stage interviews with teachers, as well as a literature on survey design for social network surveys. The existing literature suggested a number of ways to increase the validity and reliability of an online personal network survey through survey design, including suggested question formatting, Likert scale formatting, and graphical display of the survey (Coromina & Coenders, 2006; Matzat & Snijders, 2010). For example, when survey respondents were asked to provide information on people they nominated as part of their network (alters), Coromina and Coenders (2006) suggest designing the survey so that respondents answer questions on one characteristic for all alters, rather than multiple characteristics for each alter in a single question. This survey design has been found to result in a smaller percentage of item non-response and lessen respondent drop-out rates. We analyzed pilot survey data to explore potential correlations among variables of interest, including retention, self-efficacy, and network metrics (e.g., network density).

Following the design, distribution, and analysis of the pilot survey data, we conducted 60-min cognitive interviews with three pilot survey participants. Cognitive interviews are commonly used to identify problems with items for structured instruments, aiding in instrument development, and therefore were an important component of our validation process (Knafl, 2008). In this study, we used cognitive interviews to assess participant understanding of survey items, understand their thought process while answering survey items, and explore alternative options on survey items. During the cognitive interviews, interviewers asked participants to read each survey item aloud and then asked, "please describe, in your own words, what this question is asking." The interviewer then probed teacher responses to elicit teacher thinking behind the response, determine whether alternative responses were considered, and identify any specific areas of confusion. Follow-up questions prompted teachers to elaborate on their responses and address areas where the research team was particularly interested in how teachers interpreted and thought about survey items. For example, in discussing the section of the survey where teachers were asked to indicate the types of support provided by alters, the interviewer asked, "was it difficult to determine the type of support offered by each person?" After interviews were complete, we summarized cognitive interview data using a content-analytic summary table (Miles et al., 2019) that synthesized responses across teachers by survey item. This process allowed us to understand respondent thought processes when reading survey items, develop an understanding of answer choices, and provided the ability to identify areas of confusion or possible missing information.

Based on the results of the cognitive interviews and pilot testing, we revised, added, or removed survey items to finalize the TPNS. Revisions tended to address minor typographical errors and occasional issues with definitions or wording. For example, we found that the original response options for alter associations where teachers indicate how they know each person in their network (e.g., "currently works at school", "currently works at another school", "I know from outside my career") were, to varying degrees, confusing to teachers and did not seem to accurately capture how teachers knew alters.

Using this data, we revised this item to replace the "I know from outside my career" with an "Other" option and added follow-up questions to more precisely determine how teachers were associated with each alter in their network.

Measures

Name generator

The main interest in this study was teachers' support networks. Therefore, we developed multiple questions on the TPNS, through the validation process previously described, to explore teachers' personal networks. To develop teachers' personal support networks, respondents first answered a name generator question to elicit names of those within their support network, or their alters ("Who has supported you as a teacher?"). We designed the name generator question to capture a broad range of support alters, including both strong and weak ties, to develop an understanding of network composition. Based on the findings from the pilot study and subsequent cognitive interviews, the final TPNS restricted the maximum number of alters respondents could provide in the name generator to 20. The instructions prompted respondents to consider people both within and outside of their school, within and outside education, and to list as many names as needed to accurately depict their support network. We purposely did not define the term "support" in the name generator question in an effort to elicit a full ego-centric support network from respondents.

Name interpreters

After answering the name generator question, respondents completed name interpreter questions, which were designed to elicit more information regarding the alters in a teacher's support network. A name interpreter is meant to gather the relevant information about alters in a network, such as modes of communication, demographic information, and other factors specific to the research questions of interest. The name interpreter items were auto-filled with the names entered by the respondent in the name generator question, allowing the respondent to provide information on each alter individually. Following the recommendations of Coromina and Coenders (2006), we formatted the name interpreter questions such that respondents answer questions on one characteristic for all alters at the same time.

For the purposes of the research presented here, we focused on four alter and tie characteristics that were included in the models as independent variables, including alter gender, alter association with the Noyce program, how an ego knows an alter, and ego–alter closeness. Alter gender (GEN_A) was binary, with the value "1" assigned for female and "0" as the reference category. Alters' association with the Noyce program (ASSOC) was also binary, with the value "1" for alters who are or were associated with the Noyce program and "0" as the reference category. A binary variable indicating how an ego knows an alter (KNOW_CAR) was used, with the value "1" representing alters that a respondent knew from their career (e.g., teachers, principals, assistant principals, etc.) and "0" representing alters that an ego did not know from their career (e.g., spouse, family, friends, faculty advisors, etc.). Ego–alter closeness (CLOSE) was a continuous variable representing the strength of the tie between the teacher (i.e., ego) and a support alter, such that closeness was ranked on a 4-point Likert scale where 1 = distant and 4 = especially close.

Teacher and program characteristics

In addition to variables related to the alter and tie characteristics, we examined the respondent's time teaching and their exposure to various Noyce program characteristics. Time teaching was a binary independent variable where teachers who taught for 3 years or less were considered to be novice teachers and teachers who taught for 4 or more years were considered to be experienced teachers. This variable (NOVICE) was assigned a value of "1" for novice teachers and "0" for experienced teachers. In this dataset, 103 teachers (62.4%) were novice teachers and the remaining 62 (37.6%) teachers were experienced teachers. We represented exposure to Noyce characteristics with a series of variables that represented program characteristics most commonly associated with Noyce programs. Through the survey validation process, we identified 13 characteristics that are common in Noyce programs throughout the United States. Note that although these characteristics were identified as being specific to Noyce programs, they are activities that are often integrated into teacher preparation programs, and therefore, provide valuable information regarding how preservice teachers' exposure to specific activities may impact their mentor support networks when they become early career teachers. Each of the 13 variables that represented an identified Noyce characteristic was binary, with a value of "1" indicating that the respondent did have exposure to a given Noyce activity or resource and a value of "0" indicating that the respondent did not. More information about the program characteristics are provided below.

Regular meetings. Two options were provided: "Regular meetings with Noyce Scholars" and "regular meetings with mixed attendees." Noyce teachers noted that regular general meetings as part of their teacher preparation programs are different than a meeting with their Noyce cohorts that included the other Noyce Scholars. It was clear during the interviews that some programs do not provide meetings for Noyce teacher cohorts to collaborate but just add them to the larger group meetings as part of their teacher preparation programs.

Mentors. Three types of mentors were listed in the survey, including "faculty mentor" (described as faculty in the teacher preparation program), "STEM mentor" (described as a content expert), and "other mentor" (described as a mentor who was neither a faculty nor a STEM mentor).

Teacher experience. Two options were provided: "Regular teaching experience" and "teaching experience in high-need school." It was important to distinguish the experiences since teachers indicated having some experience in high-need school classrooms was helpful early in their career.

Teaching feedback. The survey question included two options: "Noyce faculty observed my teaching" and "I observed others teaching." Several teachers indicated that they had opportunities to be observed by Noyce faculty, who are the leads of their Noyce programs. Additionally, as part of the program requirement, they observed teachers in the classroom.

Finding a teaching job. Again, two options were provided, including whether the program provided a guaranteed teaching job as a program component and/or provided assistance finding a teaching job.

Induction program. Lastly, we asked if the program provided an induction program.

Dependent variable

Through the survey, we asked respondents, "for each person you listed, please indicate which type of support the person provides you with as a teacher", and provided a list of support types, finalized using the previously described pilot survey and cognitive interviews. For the purposes of this study, the dependent variable of interest was Mentorship/Coaching support, hereby referred to as mentor support (MENT). MENT was a binary dependent variable, where a value of "1" indicates that the respondent received mentor support from a specified alter and "0" indicates that the respondent did not receive mentor support from a specified alter. The dependent variable was well-balanced, with about 54% of ties representing mentor support provided to the ego by an alter.

Data analysis

Given the personal network approach utilized in this study, the resulting dataset comprised 165 egos, each of whom provided their own set of alters. Therefore, each ego produced a network independent from the networks provided by other egos. Personal network data such as this have a clear hierarchical data structure, where the network alters and the ties between a given ego and their specified alters (Level 1) are purely nested within egos (Level 2; Vacca, 2018). In such a data structure, it is likely that the alters and the network ties associated with one survey respondent, or ego, are more alike to each other than those associated with another ego. Thus, the use of a traditional regression model that ignores clustering can lead to a violation of the assumption of independence of observations and result in biased estimates of the standard errors (Raudenbush & Bryk, 2002). Therefore, personal network survey data should be treated as multilevel and a hierarchical linear model can be used to appropriately model the dependent variable at Level 1 (Snijders et al., 1995; Vacca, 2018). In this study, the dependent variable is binary, and therefore, we adopted a hierarchical generalized linear model (HGLM) to appropriately examine the relationship between the independent variables and mentorship support.

This study employed a series of two-level HGLM analyses, where Level-1 variables included those associated with network alters or ties and the Level-2 variable was associated with the ego. The outcome, mentor support, was placed at Level 1 as it is represented by the tie connecting an ego to its alter. The simplest conditional Level-1 model, with only one covariate, can be represented by,

$$\log\left(\frac{p_{ij}}{1-p_{ij}}\right) = \beta_{0j} + \beta_{1j}X_{ij}, \tag{1}$$

where $\log\left(\frac{p_{ij}}{1-p}\right)$ represents the logit of the probability, p_{ij}, that a tie, i, affiliated with an ego, j, is perceived by the ego as providing them with mentor support. β_{1j} represents the impact of the Level-1 predictor, X_{ij}, on the log odds of an alter providing an ego with mentor support per unit increase in X_{ij}, and β_{0j} is the intercept for ego j. The Level-1 model can be extended to include multiple predictors. Additionally, β_{0j} is the ego-specific intercept parameter. The conditional Level-2 model with a single Level-2 predictor and random intercept can be represented by,

$$\begin{cases} \beta_{0j} = \gamma_{00} + \gamma_{01}Z_j + u_{0j} \\ \beta_{1j} = \gamma_{10} \end{cases}, \tag{2}$$

where γ_{00} is the average log odds of having a mentor support tie across all alters and all egos, γ_{01} is the average change in the intercept per unit change in the Level-2 predictor,Z_j, controlling for all other covariates included in the model, and γ_{10} represents the average change in mentor support per one unit increase of the Level-1 predictor, X_{ij}. The Level-2 model can be extended to include multiple predictors in either the intercept or slope equations. The random effect, u_{0j}, represents the random variation in Level-2 clusters (i.e., egos), or in other words, the effect of clustering, which is assumed to be normally distributed with a mean of 0 and variance, σ_u^2. Random slopes were not estimated in this study.

First, we specified a null HGLM and then calculated the intraclass correlation coefficient (ICC) to assess the appropriateness of using a multilevel model to analyze this data. Given the binary dependent variable, we calculated the ICC using the following formula: $\sigma_u^2/(\sigma_u^2 + \frac{\pi^2}{3})$, where σ_u^2 is the variance in mentorship support between egos (Level 2) and $\frac{\pi^2}{3}$ is the variance within-ego (Level 1). In this formulation, the Level-1 error terms are assumed to follow a standard logistic distribution due to the binary outcome. The first conditional HGLM included the main effects of Level-1 covariates. Following the recommendations provided by Enders and Tofighi (2007), all covariates at Level 1, including dummy variables, were grand-mean centered. The model was refined by examining statistical significance of the main effects and excluding covariates that were not statistically significant in later models (Enders & Tofighi, 2007). Next, we added conceivable interactions at Level 1 and examined for statistical significance. When a Level-1 model was selected, we followed the same procedure for adding covariates to the Level-2 model. The binary variable at Level 2 was left its raw form (Enders & Tofighi, 2007). We fit all models in this study using the default settings for the package *lme4* in R.

Additionally, we conducted a series of Pearson correlations to explore possible associations that may exist between the dependent variable and the 13 Noyce program characteristics. Given the multilevel data structure, it was necessary to aggregate the tie-level variable, mentorship support, to the ego-level, such that the new variable represented the proportion of network ties that represented mentorship support in a given teacher's network. For example, if a teacher's network consisted of 10 ties to alters and 5 of those ties represented mentorship support the new variable would indicate that 50% of ties to other people in that teacher's network represented mentorship support ties.

Results

Research Question 1: support network composition

We conducted descriptive statistical analysis to explore the network composition for all teachers included in this study. Across all ego-networks, 36% of alters were individuals employed at the same preK-12 school as the ego and 24% were individuals employed at a different preK-12 school than the ego. Among all alters in the sample, those who were employed by a preK-12 school were primarily teachers (45%). To a lesser extent, alters were also principals (5%), assistant principals (3%), instructional coaches (2%), or para-professionals/other support professionals (1%). Additionally, 40% of alters were people other than those employed by a preK-12 school. Among all alters in the sample, 20% were former professors or advisors. To a lesser extent, alters were also spouses (4%), family members other than a spouse (7%), friends (2%), or former colleagues (3%). Additionally, the survey prompted teachers to indicate whether or not the individuals in their personal network were or are affiliated with the Noyce program. Across all networks, an average of 24% of alters were or are affiliated with the Noyce program. Among those 24% of alters identified as being affiliated with a Noyce program, 36% were university faculty, 26% were other fellows or scholars, 20% were program administrators, and 18% served multiple roles.

Table 2 provides further information regarding the network composition of novice and more experienced teachers, separately. The sample included 103 (37.6%) novice teachers and 62 (62.4%) experienced teachers. Novice teachers had an average network size of 6.67 alters and more experienced teachers had an average network size of 7.98 alters. An independent *t*-test indicated that the mean network size of novice teachers was not statistically significantly different from that of more experienced

Table 2 Comparing network composition among novice and experienced teachers

Network composition variable	Novice teachers		Experienced teachers	
	n	%	*n*	%
Alter K12 affiliation				
Same school as ego	264	38.5	156	31.6
Different school as ego	136	19.8	149	30.2
Not K12 affiliated	286	41.7	188	38.1
Alter K12 position				
Teacher	301	43.8	225	45.5
Principal	29	4.2	28	5.7
Assistant principal	20	3.0	21	4.0
Instructional coach	13	1.9	6	1.2
Paraprofessional/other support professional	1	0.0	10	2.0
Alter relationship (non-K12)				
Former professor or advisor	167	24.3	68	13.7
Spouse	20	2.9	24	4.8
Family member (not spouse)	44	6.4	39	7.9
Friend	16	2.3	9	1.8
Former colleague	13	1.9	18	3.6
Affiliation with Noyce Program				
Affiliated with Noyce	186	27.3	100	20.2

The proportions represent the proportion of all alters in novice ($n=687$ alters) and experienced ($n=495$ alters) teachers' networks, respectively, for which data are available on the network composition variable teachers, $t(106.24) = 1.65$, $p = 0.10$. Experienced teachers had a notably larger proportion of alters in their network who have careers in education but are in different schools from their own, while novice teachers' networks were more likely to include people from the same school that they work in or others unaffiliated with K-12 education. Notably, when the relationship of the alter to the ego was explored in greater detail, novice teachers' networks appeared to have a greater proportion of former professors or advisors than the networks of more experienced teachers; however, in both cases, the majority of alters in the networks were other teachers.

We conducted a multilevel analysis to further explore how network composition and years of experience teaching impacted the likelihood that an ego received mentor support from the alters in their network.

Null and intermediate multilevel models

Table 3 provides the parameter estimates for Models 1 through 3. First, we fit the null, or empty model (Model 0) to the data and yielded an ICC of 0.25, indicating that 25% of the variance in mentor support is attributable to variability among egos; therefore, a multilevel model was deemed to be appropriate for this analysis. In Model 1, we included only the main effects of Level-1 covariates (GEN_A, ASSOC, KNOW_CAR, CLOSE) in the model to examine what alter and tie characteristics (i.e., the network composition) impacted the likelihood of an ego receiving mentor support. We then fit Model 2 to the data and examined both the main effects (ASSOC, NOYCE_CAR, CLOSE) and two-way interactions (KNOW_CAR x ASSOC, ASSOC x CLOSE, KNOW_CAR x CLOSE) between statistically significant variables in Model 1, and the main effects and interactions found to be statistically significant were carried forward to Model 3, which represented the final Level-1 model. In Model 3, both main effects and interactions were statistically significant. However, the results from the Level-1 model were not interpreted, as our interest here was to build the model and later interpret the results when the final multilevel model was constructed.

Full model

We used the full model to understand how novice Noyce teachers' mentor support networks compared to those of experienced Noyce teachers (Research Question 1), which also provides information regarding who is most likely to provide mentor support to Noyce teachers. Table 4 provides the parameter estimates for Model 4, which included the addition of the relevant Level-2 covariate grouping teachers as novice or experienced (NOVICE). Model 4 included the selected Level-1 model and the main effect for the Level-2 variable and represented the full model. The inclusion of NOVICE at Level 2 of the model allowed for the examination of differences in the likelihood of receiving mentor support through alters in an ego's network that may exist between novice teachers and experienced teachers.

The final model resulted in a statistically significant interaction between how an ego knows an alter in their support network (KNOW_CAR) and how close an ego feels to an alter (CLOSE), which indicated that when an ego knew an alter from their teaching career, the likelihood that the alter provided mentor support increased as the ego's average perceived closeness to an alter increased. Conversely, when an ego did not know an alter from their career, the likelihood that the alter provided mentor support decreased as the ego's average perceived

Table 3 Level-1 models with alter and tie characteristics

Variable	Model 1			Model 2			Model 3		
	Est	SE	OR	Est	SE	OR	Est	SE	OR
Fixed effects									
Intercept	0.368**	0.12	1.44	0.214	0.12	1.24	0.211	0.12	1.24
GEN_A	0.186	0.15	1.20						
ASSOC	0.541**	0.18	1.72	0.057	0.20	1.06	0.057	0.20	1.06
KNOW_CAR	0.574***	0.15	1.77	0.505**	0.17	1.66	0.577***	0.16	1.78
CLOSE	− 0.267***	0.08	0.76	− 0.158	0.08	0.85	− 0.184*	0.08	0.83
KNOW_CAR x ASSOC				− 2.195***	0.41	0.11	− 1.976***	0.39	0.14
ASSOC x CLOSE				0.398	0.21	1.49			
KNOW_CAR x CLOSE				0.913***	0.17	2.50	0.863***	0.16	2.37
Random effect									
Between-clusters	1.17			1.20			1.23		

Note. Est = coefficient estimate

*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$

Table 4 Parameter estimates for multilevel models with ego-characteristics

Characteristic	Model 4		
	Est	SE	OR
Alter and tie characteristics			
Intercept	− 0.2687	0.18	0.76
ASSOC	0.0389	0.20	1.04
KNOW_CAR	0.5933***	0.16	1.81
CLOSE	− 0.1873*	0.08	0.83
KNOW_CAR x ASSOC	− 1.9206***	0.38	0.15
KNOW_CAR x CLOSE	0.8717***	0.16	2.39
Ego characteristics			
NOVICE	0.7733**	0.23	2.16
Random effect			
Between-clusters	1.016		

Est coefficient estimate

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Table 5 Descriptive statistics for Noyce program characteristics

Program characteristic	*n*	%	*r*
Regular meetings with Noyce scholars	80	48.8	0.19*
Regular meetings with mixed attendees	59	36.0	0.19*
Provided faculty mentor	123	75.0	0.18*
Provided STEM mentor	65	39.6	0.18*
Provided other mentor	88	53.7	0.24**
Student teaching experience	43	26.2	0.12
Student teaching experience in a high-need school	102	62.2	− 0.03
Participated in PLC	88	53.7	0.03
Noyce faculty observed my teaching	113	68.9	0.09
I observed others teaching	92	56.0	0.02
Provided a guaranteed job	29	17.7	0.20**
Provided assistance finding a job	96	58.5	0.13
Participated in induction program	82	50.0	0.04

r = Pearson correlation coefficient representing the correlation between exposure to a Noyce program characteristic and the average number of mentor ties in a teacher's network. n_{exp} = number of teachers exposed to a given program characteristic. $n = 164$

*$p < 0.05$, **$p < 0.01$

closeness to an alter increased. We also found a statistically significant interaction between whether or not an alter was associated with the Noyce program (ASSOC) and how an ego knew an alter in their support network, such that when an ego knew an alter from their career, the likelihood that an alter provided mentor support decreased if an alter was associated with the Noyce program. However, if an ego did not know an alter from their career, the likelihood that an alter provided mentor support increased if an alter was associated with the Noyce program. In other words, among those alters that an ego did not know from their career (e.g., family, friends, faculty advisors, etc.), they were more likely to provide mentor support if they were also affiliated with a Noyce program than if they were not. If the ego did know an alter from their career (e.g., teachers, principals, etc.), they were more likely to be provided mentorship from those unaffiliated with Noyce than those who were affiliated with Noyce. Additionally, at the ego level, the results indicated that, when controlling for network composition variables at Level 1, novice teachers were just over two times more likely to receive mentor support from the alters in their network than their more experienced peers (OR = 2.16, $p < 0.01$).

To further understand the findings from the full model, we examined descriptive statistics to better understand how the mentor tie between an alter and an ego was related to the relationship of the alter to the ego (i.e., fellow teacher, faculty advisor, etc.). Among novice teachers, 60% of the connections between the teacher and their alters represented mentor ties. Of those mentor connections, the vast majority were to other teachers (45%) or to former professors/advisors (31%). Among more experienced teachers, 44% of the connections between the teacher and their alters represented mentor ties. Similar to novice teachers, of those mentor connections, the vast majority were to other teachers (45%), but a much smaller proportion of ties were to former professors/advisors (22%) as compared to novice teachers.

Research Question 2: Noyce program characteristics and mentor support

Research Question 2 addressed how exposure to Noyce program characteristics was related to an ego receiving mentor support from the alters in their support network. Table 5 provides descriptive information regarding the number and proportion of teachers who indicated that they were exposed to each Noyce program characteristic. Greater than 60% of participating teachers reported being provided a faculty mentor during their Noyce experience, having student taught in a high-need school, and having been observed by a Noyce faculty member in their classroom. Additionally, we calculated Pearson correlations examining the relationship between a teacher's exposure to each program characteristic and the proportion of mentor ties in a teacher's network. Program characteristics that indicted participants were exposed to regular Noyce meetings (both Noyce-only meetings as well as meeting with Noyce and non-Noyce participants) and were provided a mentor (Faculty, STEM, or Other type of mentor) resulted in the strongest positive correlations, suggesting that when a teacher was exposed to these program characteristics, there was an overall increase in the proportion of alters in their network who provided them with mentor support. Similarly, when teachers indicated that their Noyce program provided them with a guaranteed job, there was an increase in the proportion of alters in their network who provided them with mentor support. Exposure to other program characteristics were not significantly correlated to the proportion of ties in a teacher's network representing mentor support.

Discussion

The overall purpose of this study was to explore how the composition and characteristics of Noyce teachers' support networks impact the likelihood of receiving mentor support from their networks. Additionally, this study explored whether or not novice Noyce teachers are more or less likely than experienced Noyce teachers to receive mentorship from their support networks, and further, how exposure to various program characteristics common to Noyce programs is related to a teacher receiving mentor support from their network.

Teacher support network composition

Previous research regarding teacher support networks suggests that teachers utilize people in their networks for different purposes, often relying on teachers in their own schools for day-to-day tasks associated with teaching and school norms and practices, but relying on those outside of their school for support more broadly associated with their growth as a professional in the field of education (Baker-Doyle, 2012). The findings of this study support and extend this literature within the context of the Noyce program and teacher social networks. The findings in this study show that the relationships that teachers have with others within their support network that pre-date their in-service teaching career are more likely to provide mentor support if they are affiliated with the teacher's teacher preparation program. Descriptive results provide further insights regarding this finding, and suggest that, when compared to their more experienced colleagues, novice teachers may rely on mentorship support from former faculty and advisors more often, suggesting that university faculty or advisors met through the Noyce program remain important mentors within novice teachers' support networks following graduation from the teacher preparation program. In contrast, the findings show that in-service teachers do not appear to rely on colleagues who are fellow Noyce participants to provide mentor support as a part of their support network; instead, mentor support is more often provided by colleagues, especially other teachers, who are not affiliated with their teacher preparation program. Although this exploratory study cannot draw conclusions about why teachers reported mentor support from some sources and not others, this reliance on school colleagues over fellow Noyce participants may be due to a particular need for localized mentorship within teachers' particular school contexts or perhaps a greater level of teaching experience or expertise among more veteran school colleagues.

Additionally, the results indicate that in-service Noyce teachers are more likely to receive mentor support from their colleagues in a teaching career that they feel close to; however, among those people in their support network that they know from outside of their career, the likelihood that those people provide mentor support to a teacher decreases the closer they feel to that person. Again, when we further examine network composition in regard to mentor ties, it is apparent that, among those people within a teachers' network who are not their colleagues in a K-12 school, former faculty or advisors provide the most mentor support. Therefore, this finding suggests that teachers do not necessarily need to have a particularly close relationships with mentors they acquired from their academic studies. In contrast, teachers are more likely to receive mentor support among colleagues when they perceive that they have particularly close relationships with those colleagues. Here, other teachers were primary givers of mentorship support to in-service Noyce teachers, as opposed to school administration or other colleagues. According to Baker-Doyle (2012), it is likely that such relationships develop to navigate the in-school environment, providing the teacher with information that helps them to collaborate, problem-solve, and navigate school-level politics.

Novice teachers, Noyce program characteristics, and mentoring support

Numerous studies have suggested that novice teachers, or those with 3 years or less of teaching experience, are more likely to remain in their schools or in a teaching career more generally if they had a mentor in their teacher preparation program (Smith & Ingersoll, 2004). Interestingly, on average, novice and experienced Noyce teachers in this study have similarly sized support networks. However, the ways in which they use those networks differ. Overall, novice teachers in this sample are indeed more likely to obtain mentor support from their larger support network than more experienced teachers. While more experienced teachers in this study generally draw mentorship support from K-12 education colleagues within and outside of their school, novice teachers receive a larger share of mentorship from people they know from their teacher preparation programs, specifically former faculty and advisors.

The findings also suggest that certain program characteristics of Noyce programs may be related to whether or not in-service Noyce teachers receive mentor support. This could also influence teachers social network structure. Noyce programs that offer more support around mentoring support and opportunities to network with others in meetings, might influence teachers' networks. Unsurprisingly, being assigned a mentor, regardless of the type of mentor, is related to the proportion of mentorship ties in a teacher's network. This suggests that it is possible that following graduation from a Noyce program, teachers who were provided some type of mentor retain that mentorship relationship as they begin their career as an in-service teacher. Additionally, many Noyce programs offer induction programs where mentors can continue to support teachers. The literature highlights the importance of induction programs, and specifically the ways in which they support mentorship, with participants in induction programs describing the mentorship component of these programs as helpful and important, and this is supported by additional data on the positive relationship between mentorship and retention among early-career teachers (D'Amico et al., 2020; Huling et al., 2012; Hutchison, 2012; Ingersoll & Kralik, 2004; Ingersoll & Strong, 2011). Additionally, having regular meetings as a part of the Noyce program is positively related to the proportion of ties in a teacher's network that represent mentor support. This finding has important implications for Noyce programs, as the structure of the program and the inclusion of regularly scheduled meetings with scholars is not specified as a condition of funding. For example, some Noyce programs are integrated into pre-existing teacher preparation programs, and therefore, funding is not specifically used for programming, but rather, for recruitment and other needs. In fact, less than half of teachers in this study reported that their Noyce program was structured such that regular meetings occurred, either with other Noyce scholars alone or with other non-Noyce participants. Lastly, a very small percentage of Noyce programs attended by the teachers in this sample guide their scholars with assistance finding a teaching job, which is an important support need for early career teachers from their mentors. This infrequent assistance with finding a teaching job is particularly important since our other study findings indicate that when programs such as Noyce do help teachers find teaching jobs, it increases teachers' intentions to remain in the teaching field (Alemdar et al., 2022). Thus, teacher preparation programs' relationship with school districts and their knowledge and understanding of the community would be useful to place new teachers in a supportive environment. Additional research is needed to more closely examine the nature of mentorship relationships and specific types of support mentors provided during the transition period between pre- and in-service teaching.

Limitations

This study does not come without limitations. Firstly, the larger study from which the data for this study was taken is an exploratory study. The purpose of the larger study was not to assess causal links between teacher retention or personal networks; instead, it was to explore possible relationships that may exist among attributes of the alters, relationships between teachers and their alters, and attributes of the teachers themselves. Therefore, the associations described in this study should not be used as definitive guidance for designing teacher preparation programs with the goal of increasing mentor support as graduates transition to become in-service teachers. Rather, future research may use these results to further examine and understand how factors related to the composition of teacher's support networks and characteristics of teacher preparation programs may increase mentor support for graduates of their programs. Furthermore, although this study included a sample of teachers from numerous Noyce programs throughout the United States, the results of this study would not be considered generalizable to teacher preparation programs beyond the Noyce program. However, the results provide insights into potentially impactful components of teacher preparation programs and how they could be useful to support novice teachers in the field. The results also highlight the importance of considering how the design of teacher preparation programs may contribute to continued mentorship support. The sample of teacher participants in this study are from a single type of program with specific funding requirements that inform scholar's experiences in the program and their in-service teacher experiences following the program. As a result, participants in this study may be categorically different from teachers who graduated from other teacher preparation programs and the results should not be generalized to all teacher preparation programs, or all teachers. Additionally, the purpose of this study was not to assess all the various ways that a teacher preparation program may impact teacher's support networks or their likelihood of receiving mentor support from those networks. The results here are meant to be descriptive and to provide some explanation for factors that may increase the likelihood that teachers receive mentor support from their support networks given the importance of mentorship in the literature as it pertains to teacher retention.

Conclusion

This study offers some initial insights into the impact that teacher preparation programs can have on teachers' mentor support networks, specifically within the Noyce program. Research shows that mentor support has important implications for teacher retention

(D'Amico et al., 2020; Oliver, 2015), but little work has specifically examined the ways in which teacher preparation programs may increase mentor support among early career teachers, and further, how the composition of a teacher's support network may relate specifically to mentor support. As such, this study contributes to the field's understanding of how the characteristics of a teacher's support network may impact their likelihood of receiving mentor support, and furthermore, how teacher preparation programs may facilitate the development of a network that increases the likelihood of mentor support among teachers. These findings illustrate the value of mentorship for teachers. Further research is needed to understand how the specific mechanisms, duration, and format of induction or mentorship programs may influence teachers' support system, as well as how these elements interact with the school and individual characteristics associated with teacher retention. Additionally, future research could focus on investigating the role of mentoring and teacher support networks for early career teachers in non-STEM teaching fields. The understanding of the network compositions of non-STEM teachers would provide an opportunity to conduct a comparison study with STEM teachers.

Abbreviations
STEM: Science, technology, engineering, and mathematics; SNA: Social network analysis; TPNS: Teacher Personal Network Survey; HGLM: Hierarchical generalized linear model.

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Author contributions
M.A. contributed to the writing and editing of all sections of the manuscript, analysis of data, and construction of tables. C.C. contributed to the writing and editing of all sections of the manuscript, analysis of data, and construction of tables. J.G. contributed to the writing of the introductory sections of the manuscript, results, and discussion. K.B. contributed to the writing of the introductory sections of the manuscript, specifically focusing on the literature review. All authors read and approved the final manuscript.

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Availability of data and materials
The data sets generated and analyzed during the study are not publicly available due to the sensitivity of the identified data.

Declarations

Ethics approval and consent to participate
This study was approved by the IRB at Georgia Institute of Technology, protocol number H17329.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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