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Brandon Ofem
University of Missouri-St. Louis, brandonofem@gmail.com

Michael Beeth
University of Wisconsin Oshkosh, beeth@uwosh.edu

Jessica Doering
The Doering Institute, drjessicadoering@gmail.com

Kathleen Fink
University of Missouri-St. Louis, finkk@umsl.edu

Rebecca Konz
University of Minnesota, konzx017@umn.edu

See next page for additional authors

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Authors

Brandon Ofem, Michael Beeth, Jessica Doering, Kathleen Fink, Rebecca Konz, Margaret J. Mohr-Schroeder, Samuel J. Polizzi, Gillian Roehrig, Gregory T. Rushton, and Keith Sheppard

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Brandon Ofem
University of Missouri-St. Louis

Michael Beeth
University of Wisconsin Oshkosh

Jessica Doering
The Doering Institute

Kathleen Fink
University of Missouri-St. Louis

Rebecca Konz
University of Minnesota

Margaret J. Mohr-Schroeder
University of Kentucky

Samuel J. Polizzi
Georgia Highlands College

Gillian Roehrig
University of Minnesota

Gregory T. Rushton
Middle Tennessee State University

Keith Sheppard
Stony Brook University

ABSTRACT

The STEM teacher workforce in the United States has faced a host of pressing challenges, including teacher shortages, pervasive job dissatisfaction, and high turnover, problems largely attributable to working conditions within schools and districts. These problems have been exacerbated in high-needs districts with fewer resources and more students from low-income communities. Since social network research has shown that workplace relationships are vital for retention, this study investigates the demographic and relational antecedents to what we dub *ties of retention*. We explore how demographic and relational properties affect the likelihood that teachers have "retention-friendly" networks, characterized by connections important for retention. Our analysis of data from a sample of 120 STEM teachers across five geographic regions identifies key demographics (i.e., site, gender, career changer, and prior teaching experience) and relational properties (network size, positive affect, and perceptions of bridging) associated with ties of retention. We discuss the implications of our findings for the STEM teacher workforce and for teacher education programs.

"I think another thing as far as retention of teachers goes is department/dynamics/support/cohesiveness. It makes a world of difference to have coworkers that are supportive. And difficult coworkers can make work miserable. New teachers often are hesitant to go to administration for help but are more willing to ask a veteran teacher and not feel judged, so building those relationships among teachers is key." (Jenny Blue, High School Science Teacher).

There have been historic and persistent shortages of teachers in the US workforce, a problem that has worsened due to the COVID-19 pandemic (Bailey & Schurz, 2020; Hutchison, 2012; Lachlan et al., 2020; Steiner & Woo, 2021; Sutcher et al., 2016). The problem has been exacerbated by high turnover among new teachers and is especially salient among science, technology, engineering, and mathematics (STEM) teachers working in high-needs districts (Ingersoll et al., 2021; Ingersoll & Strong, 2011; Sutcher et al., 2016). This is a national concern since students from low-income communities especially need good role models and quality education for economic empowerment and upward mobility (Berry, 2008; Gershenson et al., 2018; Ofem et al., 2021). Instability in a school's teacher workforce negatively affects student achievement, diminishes teacher effectiveness and quality, and consumes economic resources that could be deployed elsewhere. Filling a vacancy costs $21,000 a year on average, costing an estimated $8 billion a year nationally (Garcia &Weiss 2019); and the opportunity costs of lower student achievement at these critical life stages could be even greater.

This study aims to advance knowledge on the ongoing high turnover problem by exploring the following research question: What workplace conditions affect the likelihood of retention among STEM teachers working in high-needs districts? Since social network research has established that workplace relationships are vital for retention (Ballinger et al., 2016), we investigate the demographic (i.e., attributes of the teachers) and relational antecedents (i.e., attributes of their relationships) to what we dub *ties of retention*. As the opening quote illustrates, promoting retention occurs through the modality of relationship. People are more likely to stay in a workplace characterized by more positive and supportive ties (Coyle, 2018). We explore how teacher demographics and properties of workplace ties affect the likelihood that teachers have "retention friendly" networks, characterized by connections identified as important for retention. We present ties of retention as a useful construct for research on turnover, and investigate its cofactors in data from a sample of 120 middle and high school science and mathematics teachers working in high-needs districts across five geographic regions in the US.

We first describe the distinctive features of social network analysis. Next, we present our methods and analysis, and document patterns we observe in our new STEM teacher dataset in predicting ties of retention. We then discuss the broad implications of our findings for theory and

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practice. We do this while making the case for the dual wielding of human and social capital approaches in tackling the voluntary turnover problem across schools and districts. Furthermore, we contend that this approach is useful for teacher educators equipping this critical workforce with the right knowledge, skills, abilities, and other characteristics (KSAOs) to succeed in their early years of in-service.

Theoretical Framework

The fundamental insight of social network analysis (SNA) is that individual behavior is best understood in the context of social relationships, which can be modeled with a social network perspective (Borgatti & Ofem, 2010). A social network consists of a set of nodes and ties, where the nodes are the social actors (e.g., people, teams, schools), and the ties are the relationships between them (e.g., friendships, information sharing, trust). The structure and composition of social networks have important implications for the social actors within them. They serve as *pipes* through which information, resources, and influence flow; *bonds* facilitating cooperative action; and *prisms* signaling status to network observers (Borgatti & Ofem 2010). The network lens has exploded across the social sciences over the past few decades, and scholars have applied it to understanding human resource outcomes such as organizational attachment and employee turnover (Ballinger et al., 2016).

For educational researchers and teacher preparation programs, this relational perspective is crucial for theory and practice. Relationships constitute the most critical feature of the workplace, so understanding how their patterning affects teachers' perceptions, attitudes, and behaviors is essential for promoting retention. The network lens provides analytical tools and constructs for diagnosing, treating, and innovatively solving problems of retention (Cross et al., 2018).

Explaining Retention

Scholarship around retention has generally followed a traditional mode of explanation in the social sciences that focuses on the characteristics of entities to predict outcomes. In this view, retention is explained in terms of how characteristics of the organization (e.g., selection processes, onboarding practices, work design, promotion and compensation packages, etc.) impact characteristics of the individual (e.g., knowledge, skills and abilities) that make them more likely to stay (Cross et al., 2018). Or, they use other characteristics of the individual (e.g., age, prior experience) to predict voluntary turnover (Ingersoll, 2001). These explanations/antecedents have an atomistic quality in the sense that individual outcomes are considered in isolation and use a *human capital* lens.

In contrast, SNA points to the importance of *social capital*, which refers to the relational advantages available to social actors due to their position within a larger network (Adler & Kwon, 2005). In this mode of explanation, characteristics of the social actor and the social environment (i.e., social network) are used to explain organizational outcomes. Over a decade of research across dozens of organizations has shown that social network measures predict retention better than typical human capital measures (Ballinger et al., 2016; Cross et al., 2018). Yet, research has only begun expanding the suite of social capital measures, beyond simple measure of network size, to explore what factors matter the most for voluntary turnover and retention for new STEM teachers across schools, districts, and/or the overall teaching profession.

In this study, we apply an egocentric approach to investigate the demographic (i.e., site of teacher preparation, prior teaching experience, career changer, age, and gender) and relational (i.e., instrumental and expressive ties) correlates of what we dub *ties of retention*, characterized by connections identified as important for retention. Thus, this study is primarily a *theory of network* study that aims to predict why some teachers report more ties identified as important for their retention than other teachers. The outcome variable we explore is based on the commonsense notion that teachers are more likely to stay in their school/profession if they have people contributing to their *perceived desirability* to remaining in their school/profession. This perceived desirability is especially critical for retaining STEM teachers in high-needs districts that face additional stressors and resource constraints.

In sum, our guiding theory is this: Demographics (i.e., characteristics of the teachers) and network properties (i.e., characteristics of their networks) both contribute to whether teachers' ego networks consist of ties deemed important for retention. Demographic and network properties are both associated with resources that help or hinder the *perceived desirability* of remaining in the school/profession, contributing to job satisfaction and retention. The dual wielding of human and social capital approaches is the best way to study and manage voluntary turnover (Cross et al., 2018). Individual differences *and* networks both matter for predicting ties of retention for new STEM teachers working in high-needs districts.

Methods

Data Collection

The study sample was drawn from a pool of teachers with recent involvement in a teacher preparation program from five higher education institutions awarded a Robert Noyce Teacher Scholarship Program grant by the National Science Foundation. The Noyce programs are designed specifically for preparing teachers to work in high-needs districts, which have more serious problems with recruitment and retention (Kirchhoff & Lawrenz, 2011). The pool of teachers in our sample completed Noyce programs that spanned institutions in the Midwest, Northeast, and Southeast parts of the United States.

We designed an online survey to capture teacher demographics (i.e., personal characteristics and attributes) and network characteristics (i.e., properties of their ego networks). To collect the demographic variables, we included items in the survey that asked about personal characteristics (e.g., age, gender, prior teaching, etc.). To collect the network variables, we used a *name generator*, followed by more detailed questions in the *name interpreter* about the nature of each teacher's professional contacts. On the basis of Coburn et al.'s (2013) finding that interactions based on teaching expertise are a sustainable feature in teacher networks, we asked each teacher this question as part of the name generator: "*Who do you interact with on matters pertaining to teaching content and/or pedagogy?*" Since professional ties occur beyond a given school, we asked this question for the school, district, state, and national levels. We then asked, as part of the name interpreter, more detailed questions about each relationship (e.g. frequency of interaction, importance to retention, etc.). These series of questions form the basis of a teacher's community of practice (CoP), which in network terminology we define as the teacher's professional *ego network*. The ego is the teacher, and the alters constitute their professional network pertaining to teaching content and/or pedagogy.

After crafting the survey, we piloted the instrument with a small group of teachers at a participating institution, which resulted in a few revisions to improve survey design and item clarity. We then distributed surveys via email to approximately 431 teachers who went through

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these various teacher preparation programs, which generated 166 responses for a completion rate of 38.5%. There were 159 full responses due to missing data in seven survey responses. Of those, 120 respondents identified working in a high needs district, and that is the focus of this analysis.

Dependent Variable

Ties of retention. This is the key variable we aim to explore the correlates of in this study. *We define ties of retention as those ties identified by a focal teacher as important for their retention in the school and/or teaching profession*. We measured ties of retention in two ways. Total strength (TS) of retention is the sum of valued ties of retention (0, 1, 2); where 0 is not important, 1 is somewhat important, and 2 is very important for a teacher's retention. These come from the network survey items that required respondents to rate the importance of each alter on a three-point, Likert-type scale. For example, if someone has three ties and all were rated as somewhat important, TS would equal 3 (1 + 1 +1). Total number (TN) of strong ties of retention is the number of ties identified as very important (1) for retention, 0 otherwise. For example, if someone has three ties and all were identified as somewhat important or not important, TN would equal 0 (0 + 0 + 0), since none of the alters (i.e., contacts) were rated as very important. TN is essentially a dichotomized variable that makes two the threshold of a very important tie. These two operationalizations allow us to get at the same idea in two different ways. The hope is that we will see consistent effects of the demographic and relational variables on these two operationalizations, adding to the robustness of our findings.

Demographics

Based on the work of Ofem et al. (2020), we considered key demographic/attribute variables that could impact perceptions of ties of retention.

Gender. Gender is measured dichotomously, with 0 representing female and 1 representing male. Gender is a social construction that affects a variety of organizational outcomes. Gendered and socialization processes could lead to differences in how teachers perceive their ego networks (i.e., more or less ties of retention).

Age. Age is measured in years as a count variable of the length of life. Age, like gender, is associated with socialization processes that could lead to differences in how teachers perceive their ego network.

Career changer. Career changer refers to whether the respondent had a previous career prior to becoming a teacher. This could affect socialization patterns and ties identified as important for retention.

Prior teaching experience. Prior teaching experience is a count measure of the total number of years teaching prior to the current school year. This, too, could affect socialization patterns and the perception of ties identified as important for retention.

Site. To explore differences across the five sites that provided teacher training, we created four dummy variables to represent the four universities. This allows us to statistically account for differences in teacher preparation, geography, and other unobservable fixed effects.

Relational Properties

Upon our knowledge of the social context (i.e., middle and high school STEM educators), a pilot test, and related literature from this context (e.g., Ofem et al., 2020), we selected measures that captured both instrumental and expressive ties. We calculated ego network size, the frequency of interaction, the expressive relation of positive affect, and perceptions of bridging (i.e., structural holes).

Network size. Network size is a count measure of the total number of alters (i.e., contacts) identified in a teacher's professional ego network (i.e., community of practice). More ties could provide more resources and social support. Conversely, too many ties could be overwhelming and/or costly for new teachers (Cross et al., 2018).

Frequency of interaction. The frequency of interaction with each alter was measured on a 5-point scale, where 1 is "once a year" and 5 is "daily." We then calculated the sum of the total level of interaction between the ego and their set of alters. This measure captures the overall level of interaction within the teacher's ego network. Greater involvement with other teachers measured through interaction could affect how teachers describe their ego network (e.g., more or less ties of retention).

Positive affect. We measured positive affect through the operationalization of *energizing ties*. We measured an energizing relationship on a 5-point scale, where 1 is "mostly de-energizes" and 5 is "mostly energizes." Energizing ties is the sum total of an ego's valued ratings of each alter along this relational dimension. This measure is based on the idea that some relationships energize and some do not (Gerbasi et al., 2015). We theorize that ego networks characterized by more positive affect, measured through energizing ties, should be more likely to consist of "ties of retention." Energizing ties, due to the psychological safety they inspire, should be more likely to co-occur with ties of retention.

Perceptions of bridging. Bridging (or brokerage) is the extent to which a person bridges different people or groups who are not connected to one another. It comes with control and information benefits. We measured this using Mehra et al.'s (2014) visual network scale. This methodological innovation in social network measurement makes it more efficient, and less burdensome on respondents, to collect network data on perceived ego network structure. It consists of stylized depictions of network properties. Figure 1 depicts the scale we used. It reflects the extent to which a teacher perceives themselves in a bridging position, meaning the extent to which they possess structural holes (i.e., a lack of connection between alters).

Analysis

Our analysis begins with a general description of the data. We provide the summary statistics of variables and the correlation matrix, and make notable observations. Next, to address our research question, we use Poisson regression to model our two measures of ties of retention, tie strength (TS) and total number (TN). This model specification is appropriate for variables with a count distribution. The ties of retention fit this criterion since both operationalizations have discrete probability distributions, as opposed to the normal distribution required for normal parametric statistical tests. Poisson regression is appropriate for outcome variables that take the form of events, counts, incidence, and rates. It is a generalized linear model (GLM) that is part of the log-linear family of statistical tests. With the assumption that a Poisson process underlies the events of interest, Poisson regression finds maximum-likelihood estimates of the β parameters (Hamilton, 2012).

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In the diagram below, there are two groups of people. The large circle that connects the two groups can be thought of as a bridge. A bridge connects two groups, or even two people, who are not connected to each other. Without the bridge, the two groups or two people would not interact.
Using the scale below, please rate the extent to which you think you occupy a bridge position in your OVERALL personal network of professional contacts related to teaching content and/or pedagogy.

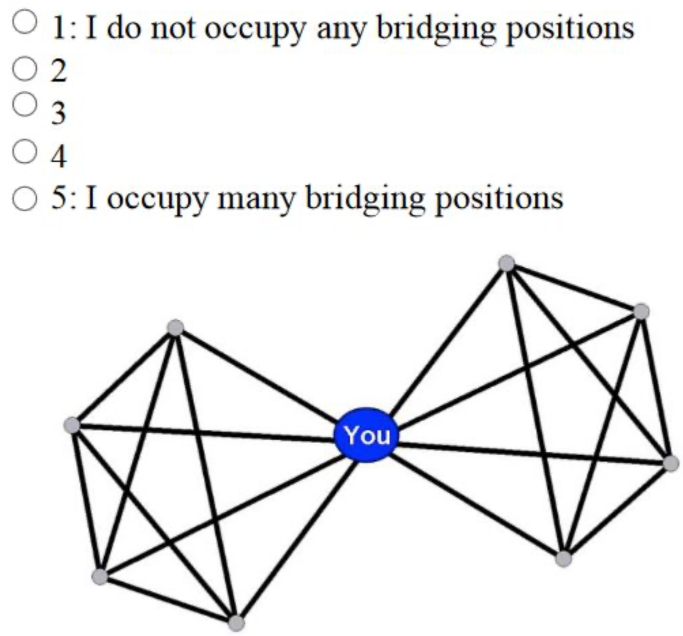

Figure 1. Visual Network Scale

Results

To paint a fuller picture of our data set, Table 1 below shows the mean, standard deviation, minima and maxima, of all the variables in this study. Table 2 is a correlation table for all the variables used in our analysis. A few notable observations: 1) A majority of the study participants are female (i.e., 61%); 2) most of the study participants have limited teaching experience (i.e., mean of 3.56); 3) approximately half of the study participants had a previous career before becoming a teacher (i.e. mean of .46); and 4) the network measures (i.e., retention strength, retention size, network size, frequency of interaction, total energizing, and bridge overall) all show significant variability in their distributions. In addition, the network variables show significant correlations with the two outcome variables, total strength (TS) and total number (TN) of ties of retention. These initial observations empirically support the premise of this article—that *properties of workplace relationships*, above and beyond sheer size, is where a lot of the cultural action is in analyzing workplace dynamics.

Table 1
Summary Statistics

	Mean	SD	Min	Max
Retention strength	9.22	7.53	0	40
Retention size	2.78	3.55	0	19
Kentucky	0.24	0.43	0	1
Minnesota	0.16	0.37	0	1
Wisconsin	0.2	0.41	0	1
Kennesaw	0.21	0.41	0	1
Gender	0.39	0.49	0	1
Age	32.98	8.17	23	63
Career changer	0.46	0.5	0	1
Years teaching	3.56	3.6	0	24
Network size	9.89	6.24	0	38
Total frequency	34.26	20.14	0	124
Total energizing	40.54	26.51	0	155
Bridge overall	2.66	0.98	1	5

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Table 2

Correlations

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Total strength (TS)													
2	Total size (TN)	0.88												
3	Kentucky	-0.14	-0.09											
4	Minnesota	0.15	0.2	-0.25										
5	Wisconsin	-0.1	-0.16	-0.28	-0.22									
6	Kennesaw	0.02	-0.03	-0.29	-0.23	-0.26								
7	Gender	0.05	0.04	-0.06	0.05	0.05	-0.09							
8	Age	-0.12	-0.15	-0.27	-0.23	0.57	0.14	0.07						
9	Career changer	-0.12	-0.18	-0.29	-0.1	0.42	0.23	-0.04	0.56					
10	Prior teaching	0.11	0.06	-0.01	-0.17	0.01	0.25	0.04	0.3	-0.12				
11	Network size	0.46	0.27	-0.16	0	-0.18	0.38	-0.12	-0.01	0.06	0.38			
12	Frequency	0.52	0.33	-0.14	0.01	-0.19	0.24	-0.1	-0.05	0.03	0.28	0.94		
13	Energizing ties	0.53	0.35	-0.18	0	-0.15	0.37	-0.13	0.01	0.08	0.37	0.98	0.93	
14	Bridging	0.2	0.14	-0.14	-0.03	-0.07	0.13	-0.07	-0.01	-0.03	0.25	0.32	0.33	0.34

$p < .05$ if $|R| > 0.19$

To better tease out the individual effects of our predictor variables on ties of retention, Table 3 shows the result of two Poisson regression models with the two operationalizations of the dependent variable (i.e., TS and TN). In regard to the demographic variables, we find statistically significant correlations with the Noyce teacher preparation site (β = .27 and .41, with p < .01 and .05, respectively); gender (β = 24 and .26, with p < .001 and .05, respectively); career changer (β = -.21 and -.36, with p < .05 and .05, respectively); prior teaching experience (β = -.04 with p < .001); (β = -.21 and -.36, with p < .05 and .05, respectively). In regard to the network properties, we find statistically significant correlations with network size (β = -.12 and -.24, with p < .001 and .001, respectively); total energizing ties (β = .04 and .07, with p < .001 and .001, respectively); and total bridging ties (β = .09 and .15, with p < .01 and .01, respectively

Table 3
Predicting Ties of Retention

	Total strength	Total number
Kentucky	-.01	-.06
Minnesota	.27**	.41*
Wisconsin	.17	-.17
Kennesaw	-.03	-.18
Gender	.24***	.26*
Age	-.01	-.01
Career changer	-.21*	-.36*
Years teaching	-.04**	-.03
Network size	-.12***	-.24***
Total frequency	.00	.00
Total energizing	.04***	.07***
Bridge overall	.09**	.15*
Constant	1.62	.36
Log likelihood	-421	-275
Pseudo R2	.25	.22

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What predicts ties of retention?

Demographics

- **Noyce teacher preparation** – Minnesota reports more ties of retention
- **Gender** – Men report more
- **Career changer** – Those who changed careers report less
- **Years teaching** – Teaching experience negatively related to one of the retention measures

Relational properties

- **Network size** – Larger networks are negatively associated
- **Energizing ties** – More positive ties are positively associated
- **Structural holes** – Bridging ties are positively associated

Figure 2. Summary of Findings

Figure 2 above summarizes our findings. In keeping with our social network approach, we again organize our predictor variables by demographics (i.e., attributes) and relational (i.e., network) properties.

Discussion

This article advances the ongoing conversation about the turnover problem among new STEM teachers, a historic and enduring problem that has surely been exacerbated by the COVID-19 pandemic (Lachlan et al., 2020; Steiner & Woo, 2021). Our goal in this paper is to demonstrate a broader way to think about turnover based on the application of a Social Network Analysis model. Instead of looking solely at characteristics of the person or features of the environment, this paper points to the importance of considering both demographic *and* network features in predicting retention. We find that demographics (i.e. site of Noyce preparation, gender, career changer, and years teaching) and network features (i.e. network size, energizing ties, and structural holes) are all correlated with ties of retention. We now consider why these effects are there. In terms of the site of the Noyce preparation site, the Minnesota site is positively related to ties of retention. This could be due to a couple processes: 1) Teachers who went through this program may be more likely to teach in disadvantaged districts, increasing the likelihood that they really need ties of support in the workplace. 2) Conversely, teachers from this site may have picked up advantageous social skills, through cohort program structures, that helped them connect early on with their peer teachers. Future work could fruitfully explore these possibilities.

In terms of gender, men report more ties of retention than women. This could be due to the underrepresentation of men in the teaching workforce and a greater need for support in tackling classroom challenges (Ofem et al., 2021). Conversely career changers and prior teaching experience are both negatively associated with ties of retention. This could be due to the greater self-efficacy and confidence that comes with a prior career and prior teaching experience. Teachers with such prior experience may be less dependent on peer teachers in carrying out their job functions. Again, future work could explore these possibilities

In terms of network properties, we find that positive affect (i.e., energizing ties) and perceptions of bridging (i.e., structural holes) increase the likelihood that new teachers identify colleagues in their workplace as important for retention. The explanation for these positive network affects can be attributed to the social capital associated with such beneficial network structures. Teachers connected to "energizing" individuals and that bridge structural holes are more likely to value their networks, increasing the likelihood that they identify others in their ego networks as "important for retention". Conversely, sheer ego network size is negatively associated with ties of retention. This could be due to the burdensome effect of having too many relational obligations.

In sum, we need to combine the traditional human capital approaches with social capital approaches in modeling voluntary turnover (Cross et al., 2018). This should include both demographics of the workforce, features of induction programs, and properties of workplace relationships. People stay at their jobs not only because they see a fit between their own background and preferences (i.e. person-environment fit), but also because of the social networks that push or pull them in certain directions (Cross et al., 2018). Our findings point to the importance of healthy relationships and culture in tackling the high school turnover problem among new STEM teachers working in high-needs districts.

Implications for Practice

Directing scholarly attention to the overall patterning/structure of teachers' professional ego networks is a useful diagnostic lens. A social network approach is aptly suited for studying and addressing problems of voluntary turnover (Ballinger et al, 2016). For example, the *ties of retention* construct, which we conceived for this study, could be a useful litmus test in diagnosing a school's culture. We would expect more positive and healthy ties and ones important for retention in schools that have healthier and more positive cultures. To build such healthy cultures, schools should focus on establishing and maintaining relationship-focused school cultures. They need to make everyone feel like they belong. Healthy cultures contribute to "energizing ties" that promote employee wellbeing and happiness, reducing the likelihood of voluntary turnover. It is the responsibility of school leaders to effectively demonstrate the social and emotional skills required to support one another (and their students) in challenging environments (Hoerr, 2020). This includes encouraging and cultivating positive ties. A growing body of evidence suggests that developing teachers' social and emotional competencies improves teacher well-being, reduces stress and burnout, and can reduce teacher turnover (Hoerr, 2020). In addition, our findings point to the importance of teachers bridging different people in their professional network. This likely gives them more autonomy and influence, contributing to their wellbeing and intention to stay in the school/profession.

In keeping with the tenets of social emotional learning (SEL; Hoerr, 2020), here are a few more specific and actionable ideas for promoting retention among new STEM teachers:

1. ***Demonstrate trust*** – Practice giving autonomy, voice, shared governance, and professional development opportunities to teachers and administrators.
2. ***Create a positive school culture***. Create policies that reward social support, peer mentoring, resilience, and boundary spanning in employees.

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3. ***Encourage the right networks at the right time***. New employees have different needs. Design targeted policies that facilitate mentorship and collegiality for employees who need it the most (Cross et al., 2018).
4. ***Measure correlates of teacher well-being, including both demographic and relational variables.*** Nearly 1 in 4 teachers reported that they were likely to leave their jobs in the 2020-2021 school year. Measuring the workplace conditions that affect that desire to leave is essential to improving turnover (Steiner & Woo, 2021).

Our study also offers some practical value for teacher educators and teacher preparation programs. Our study documents the importance of helping pre-service teachers become more cognizant of their professional networks and their effects (Korthagen et al., 2006; Polizzi et al., 2019; Polizzi et al., 2021). Our data provide evidence that networks do matter for retention, and this is information that educational policymakers and STEM teacher educators can use as they design programs to better equip our teacher workforce for the social realities of this critically important vocation (Eckman et al., 2016; Lambert et al., 2018; Theisen-Homer, 2021). Furthermore, our study opens up a new line of inquiry around our concept of "ties of retention". We encourage future work to explore this construct more deeply and further specify the relational and demographic factors associated with it.

Conclusion

This study models a social network approach to exploring the factors associated with *ties of retention*, a construct we define as workplace relationships identified as important for STEM teacher retention in the school/profession. Our analysis of 120 new STEM teachers working in predominantly disadvantaged districts reveals both demographic (i.e., teacher preparation site, gender, career changer, years teaching) and relational (i.e., network size, positive affect, and perceptions of bridging) factors associated with ties of retention. We contend that ties of retention are directly associated with the *perceived desirability* of staying, and formulate practical tips to help school leaders address the ongoing and persistent turnover problem. We further argue that this relational lens can be useful in preparing new teachers for the social realties that they will face on the job. We hope our study inspires more research that considers the demographic and relational antecedents to voluntary turnover, especially among our STEM teacher workforce in high-needs districts.

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Authors

Brandon Ofem
Associate Professor
University of Missouri-St. Louis, Global Leadership and Management Department
Email: ofemb@umsl.edu

Michael Beeth
Professor
University of Wisconsin Oshkosh, Department of Teaching and Learning
Email: *beeth@uwosh.edu*

Jessica Doering
Founder and President
The Doering Institute
Email: drjessicadoering@gmail.com

Kathleen Fink
Distinguished Teaching Professor
University of Missouri-St. Louis, College of Education
Email: finkk@umsl.edu

Rebecca Konz
PhD Candidate
University of Minnesota, Department of Curriculum and Instruction
Email: konzx017@umn.edu

Margaret J. Mohr-Schroeder
Professor of STEM Education & Senior Associate Dean
University of Kentucky, Department of STEM Education
Email: m.mohr@uky.edu

Samuel J. Polizzi
Assistant Professor & Chair of Mathematics and Physical Sciences
Georgia Highlands College, School of STEM
Email: jpolizzi@highlands.edu

Gillian Roehrig
Professor
University of Minnesota, Department of Curriculum and Instruction
Email: roehr013@umn.edu

Gregory T. Rushton
Director
Middle Tennessee State University, TN STEM Education Center
Email: Gregory.Rushton@mtsu.edu

Keith Sheppard
Associate Professor and Director
Stony Brook University, Institute for STEM Education
Email: keith.sheppard@stonybrook.edu

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