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Research paper

(Second career) teachers' work socialization as a networked process: New empirical and methodological insights

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HIGHLIGHTS

- The number of interactions and the ease of access to colleagues were both predictors of teachers' work socialization.
- Social capital seemed more important in the work socialization process for second than for first career teachers.
- The multiple membership social network model was more accurate than a single-level linear model.

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ABSTRACT

This paper uses a quantitative social network perspective to provide insights on the importance of professional interactions for (second career) teachers' work socialization. Given the lack of statistical models addressing the relation between network data and individual variables, we drew on a multiple-membership social network model (MMMCSNA) to address our research questions. Our results show the importance of social capital in the process of teachers' work socialization, even more so in the case of second career teachers. Moreover, as shown through a comparison between estimates in our MMMCSNA model and in a single-level regression model, the proposed model performed better.

1. Introduction

Due to growing teacher shortages, governments worldwide have implemented alternative certification programs (Zirkle & Jeffery, 2017) and policies to make entry into the teaching profession more flexible (Mathou, Sarazin, & Dumay, 2020; OECD, 2021). As a result, the proportion of second career teachers (SCTs) in the teaching workforce is increasing worldwide. SCTs can be defined as professionals who left a prior occupation to become teachers as a second career choice (Trent, 2018). They currently represent approximately 25% of new teachers in the US (Redding & Smith, 2016); 27% of new teachers in secondary schools in the UK (Paniagua & Sánchez-Martí, 2018); 10% of new teachers in Israel (Paniagua & Sánchez-Martí, 2018); and approximately 40% of new teachers in secondary schools in French-speaking Belgium (FWB Administration of Education, 2021). Because of their professional background and job-related expertise, the majority of SCTs enter schools offering technical and vocational education and training (TVET) programs (Gautié, 2013; Holgado, 2019; OECD, 2021). These schools are also most affected by teacher shortages (OECD, 2021).

Beyond seeing SCTs as a promising solution for the problem of teacher shortages, researchers have described them as adding value to educational quality in general (Haggard, Slostad, & Winterton, 2006; OECD, 2021). In addition to transferring practical and very specialized (often technical or vocational) expertise and knowledge from their prior jobs into the school curriculum (Troesch & Bauer, 2017), they can also bring transversal skills such as communication, management, or other organizational skills (Salyer, 2003). Therefore, SCTs are often presented as resources for school and curriculum improvement (Wilkins & Comber, 2015). In a recent systematic literature review, Ruitenburg and Tigchelaar (2021) emphasized the importance of recognizing what SCTs have to offer for school improvement. In the same vein, Wilkins and

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Comber highlighted that “initiatives to attract ECCs [‘elite’ career-changers/SCTs] into teaching are based on the presumption that they bring ‘added-value’ not just to the classroom, but to wider institutional culture and practices (…) they have the potential to become effective change agents” (Wilkins & Comber, 2015, p. 1026).

These two arguments (i.e., SCTs as solutions for teacher shortages and as change agents) depict SCTs as very important for educational systems (Wilkins & Comber, 2015). Yet, while governments are capable of attracting and recruiting SCTs into the teaching profession, they are less effective at retaining them. Research evidence has shown that SCTs suffer from a high attrition rate (Redding & Smith, 2016). They are twice as likely as first career teachers (FCTs) to leave the profession during their first five years (Chambers Mack, Johnson, Jones-Rincon, Tsatenawa, & Howard, 2019), mainly because their specific needs are not recognized (Rose & Sughrue, 2020). Research has suggested that because of their age and expected experience, they often do not receive support, as if they should be able to manage this new job alone (Bar-Tal, Chamo, Ram, Snapir, & Gilat, 2019). Several additional elements can help to explain this high attrition rate. Among these, some have been well presented in the literature: SCTs often do not occupy a secure job position, which is stressful and does not guarantee a full-time job (OECD, 2021); for some of them, their initial motivation to change careers does not match with the teaching job realities, making the “reality shock” a disappointing awareness-raising (Coppe, März, Coertjens, & Raemdonck, 2021); and finally, they struggle to fully integrate and familiarize themselves with their new profession and with the school as a new workplace (Lee, 2011; Rose & Sughrue, 2020), adding to the complexity of their induction process (OECD, 2021). In a recent study, Coppe, März, and Raemdonck (2021) concluded that the complexity of novice SCTs’ induction process can be explained by the lack of professional interactions they experience, meaning that they lack opportunities to have work-related discussions with colleagues or to ask for job-related advice. Day-to-day professional exchanges with colleagues have been reported by SCTs as one of the most useful sources of learning and professional development (Csíkos, Kovács, & Kereszty, 2018). Indeed, “collegiality is of extra importance to second career teachers, many of whom enter the teaching profession from the business world with its work teams and collaborative projects” (Lee, 2011, p. 4). There is a lot of evidence in the literature describing teacher induction and professional development as a social process for first career teachers (Colognesi, Van Nieuwenhoven, & Beausaert, 2020; Marz & Kelchtermans, 2020; Newberry & Allsop, 2017; Thomas, Tuytens, Devos, Kelchtermans, & Vanderlinde, 2020). Yet, more systematic and in-depth research is needed about the induction and professional development of SCTs (Ruitenburg & Tigchelaar, 2021) and the particular role of social interactions. In other words, more knowledge is needed on what we could call the *socially-embedded induction and professional development* of SCTs.

Social network approaches are particularly relevant to address such socially-embedded phenomena and have, in the past years, become mainstream in research on teachers (Baker-Doyle & Yoon, 2020). More and more studies have turned to social network approaches to understand teacher collaboration, teacher induction, teachers' support, teachers’ learning, and so forth (Moolenaar, 2012; Thomas et al., 2020). Building on the concept of social capital (Bourdieu, 1980; Coleman, 1988; Lin, 2008), these studies put at the forefront the social dimension of teacher development and, consequently, the importance of the professional networks in which teachers are embedded (Daly, Liou, & Der-Martirosian, 2020).

Social network approaches have complex theoretical foundations that imply specific methodological practices. Until now, although efforts have been made to statistically operationalize social network models related to teachers’ induction and professional development, some limitations have remained difficult to overcome (Daly et al., 2020; Moolenaar, Sleegers, & Daly, 2011; Moolenaar & Sleegers, 2010). One of the major limitations is related to the interdependence of network data. A social network is a pattern of ties (links) between nodes (actors) shaping the entire network. Each element of a network shares dependence with the others. Given the structural integrity of a social network, we can only grasp the reality that the network represents based on consideration of the *entire network* (including complex patterns of interconnections and inter-influences between actors). This is specifically true in the case of school social networks, because the structural patterns of schools are not homogeneous, meaning that collegial dynamics vary between subgroups/departments of teachers[1] (i.e., loosely coupled/departmentalized logics; De Lima, 2007; Meredith et al., 2017; Thomas et al., 2020).

In the area of teacher research, too many studies forget this crucial aspect when working quantitatively with social networks. In a way, we could say that these studies, despite strongly arguing that teachers' professional development is embedded in social networks, have partially overlooked that argued-for point when it was time to statistically operationalize that reality. This oversight implies major issues of *network validity,* meaning a failure to answer the question “Is the object we claim to be a network really treated as a network in our study?” (Froehlich & Sarazin, 2021). Educational sciences are in need of a statistical procedure to analyze the impact of particular network data such as the degree centrality of actors on individual continuous outcomes, such as teachers’ professional development, in network contexts with complex structural patterns that take into account the inherent interdependence of network data.

Regarding the increasing utilization of social networks in educational research, the importance of interactions with peers for the teaching profession, and the intrinsic social nature of their induction and professional development, this lack of suitable statistical procedures challenges researchers to develop a procedure to address questions linking social network data and individual continuous outcomes. While the social network literature has presented a range of statistical tests and models, procedures to predict continuous variables with network data have been less explored so far and need to be imported from other scientific domains (Silk et al., 2017; Tranmer, Steel, & Browne, 2014).

Based on the idea that we need more research on SCTs' induction and development as a socially embedded process and that analyzing such social phenomena requires a statistical procedure that takes into account what a network really is, this study has two aims. First, our contribution aims to give new insights on the importance of professional interactions for SCT development. To pursue this objective, we compare the relevance of professional interactions for SCTs and FCTs, knowing that professional networks have been clearly stated to be of major importance for the induction process and for the professional development of all teachers, especially early-career teachers (Kyndt, Gijbels, Grosemans, & Donche, 2016; Struyve et al., 2016; Thomas et al., 2020; Vangrieken, Meredith, Packer, & Kyndt, 2017). We operationalize teacher induction and professional development as a work socialization process (Coppe et al., 2020; Martineau, Portelance, & Presseau, 2009) and use the concept of social capital as a relevant

[1] To some extent, it is less necessary to consider a social phenomenon based on the entire network when the network is shaped by uniformly cohesive patterns of ties. In such a case, it could be hypothesized that the network influences each actor in the same way. This is not a relevant hypothesis for the school context.

concept to operationalize theoretically the importance of peers (Beausaert, Froehlich, Riley, & Gallant, 2021; Bourdieu, 1980; Coleman, 1988; Lin, 2008). Second, this study presents a transparent and replicable methodological procedure that considers the inherent structural dependence of networks (addressing the issue of data non-independence) inspired by the multiple-membership multiple-classification model to assess the link between social network data (here, centrality measures) and an individual continuous outcome (here, teachers' work socialization). These two objectives are complementary because the methodological procedure we develop (objective 2) enables us to pursue our empirical objective (objective 1). Therefore, the objectives were formulated and operationalized as follows:

Objective 1: To provide insight into the importance of peers in the work socialization process of teachers, especially for second career teachers in comparison with first career teachers.

- RQ1: To what extent does social capital predict the work socialization of teachers?
- RQ2: How does this prediction differ between first and second career teachers?

Objective 2: To provide a transparent and replicable methodology to assess the link between social network individual attributes (teachers' social capital) and individual continuous variables (teachers' work socialization).

In the following theoretical section, we present the concept of work socialization and our social network approach, from both a theoretical and methodological point of view.

2. Theoretical framework

2.1. The work socialization process

Bringing together insights from the literature on teacher professional development and from organizational sciences, teachers' work socialization can be defined as a learning and adaptation process that begins upon entry into the school as a workplace and continues throughout teachers' careers (Coppe et al., 2020; Wanberg, 2012). The work socialization process enables teachers to evolve in their professional practices and towards better adaptation to the teaching profession (Martineau et al., 2009; Uwamariya & Mukamurera, 2005). In this way, the concept of work socialization is closely related to the concept of teachers' professional development. While teachers' professional development has sometimes been conceptualized in a restricted way, referring to “transforming [teachers'] knowledge in practice for the benefit of their students' growth” (Avalos, 2011, p. 10) and focusing on teaching practices and students' learning (Evans, 2019), work socialization considers broader aspects of a given profession (Chao, 2012). This is in line with current trends in the educational literature presenting the teaching profession as a multidimensional activity embedded in an organization (Cherubini, 2009; Richards, Pennington, & Sinelnikov, 2019; Tang, Wong, & Cheng, 2016). This literature has advocated for considering teachers' professional development as no longer related only to teaching practice, but also to “competence to work in schools” (Tang, Cheng, & Wong, 2016, p. 161). Drawing on the work socialization literature provides a strong theoretical foundation to approach the teaching profession more broadly. Indeed, the concept of teachers' work socialization is relevant when assessing teachers' induction and professional development process, because it captures more exhaustively the dimensions of the teaching profession (Kearney, 2015).

Work socialization requires learning and adapting to the dimensions of the job. According to the organization science literature, these dimensions are referred to as the domains of socialization (Klein & Heuser, 2008). For teachers, there are four such domains: teaching task socialization, workgroup socialization, micropolitical climate socialization, and organization socialization (Coppe et al., 2020). *Teaching task socialization* refers to the technical aspects of the profession, such as the acquisition and the consolidation of pedagogical and didactic skills (Mukamurera, Martineau, Bouthiette, & Ndoreraho, 2013). *Workgroup socialization* refers to the collaborative aspect of the teaching job. Teachers have to integrate and become members of their school professional community (Baker-Doyle & Yoon, 2020). *Micropolitical climate socialization* refers to the ability to navigate the informal power dynamics in schools (Kelchtermans & Vanassche, 2017). *Organization socialization* refers to understanding the objectives, values, and culture of the school as a particular organization (Coppe et al., 2020).

2.2. A social network perspective: theoretical point of view

Both the scientific literature in organization science about socialization and the literature about teachers' induction and professional development have presented a strong consensus, that is, the importance of professional interactions with peers (Baker-Doyle & Yoon, 2020; Klein & Heuser, 2008; Kyndt et al., 2016; Moolenaar, 2012). A large body of empirical research on teacher induction and professional development has highlighted that teachers prefer to learn socially with their peers (Colognesi et al., 2020; Kyndt et al., 2016). Professional interactions allow teachers to learn, to improve their practice and to understand their workplaces (Shirrell, 2021). Recently, Daly et al. (2020) concluded that when teachers share knowledge within their professional school networks, they learn. In a recent paper, Van Waes, De Maeyer, Moolenaar, Van Petegem, and Van den Bossche (2018) highlighted the importance of networks for teachers' professional development. Shirrell (2021) also showed that professional interactions have a negative relationship with teacher turnover. Newberry and Allsop concluded about novice teachers: “It appears that a combination of difficult elements in a high intensity situation, will only result in a departure if there are not strong social-professional relationships intact (2017, p. 876). Colognesi and colleagues showed that the satisfaction and perseverance of teachers were more positively predicted by peer interaction than by formal support strategies (2020).

The literature on SCTs has especially highlighted the extra importance of peers for SCT professional induction and development. In reviewing the literature on second-career teachers' induction experience, Ruitenburg and Tigchelaar (2021) found that a large majority of studies found colleagues to be a source of support. Indeed, as SCTs often pass through fast alternative certification programs or enter the teaching profession without receiving any pedagogical training, most of their professional learning process occurs “on the job” (Perez-Roux & Lanéelle, 2013). This particular situation shapes their day-to-day professional life into a continual workplace learning process, even more than for first career teachers, who complete a full teacher training program before entering the job (Perez-Roux, 2010). Watters and Diezmann (2015) highlighted that professional relationships are essential for SCTs' retention. In a recent empirical study by Csíkos et al. (2018), “discussions with colleagues” were stated to be the most efficient source of professional development for SCTs. In the same vein, Rose and Sughrue (2020) highlighted that personal relationships with colleagues seem to encourage the professional development and retention of SCTs.

This importance of collegial dynamics for both first and second career teachers can be understood through the theoretical lens of social capital (Bourdieu, 1980; Coleman, 1988). From a network perspective, “social capital is defined as resources embedded in one's social networks, resources that can be accessed or mobilized through ties in the networks (Lin, 2008, p. 59). The fundamental idea of social capital is that “it is through one's ties to others that one gains access to particular expertise and resources (…) among individuals who interact frequently with one another” (Penuel, Riel, Krause, & Frank, 2009, p. 129). In a recent systematic literature review on the role of social capital for teacher learning, Demir (2021) found that the majority of studies showed the benefits of social capital for teacher professional development and successful teacher induction. They concluded that social capital promotes five categories of outcomes: teacher professional development, teacher retention, implementation of change, job satisfaction, and student achievement. Because social capital is intrinsically embedded in social relations (Daly et al., 2020), “in recent years, educational studies have been building on social network theory to understand the complex role of teacher relationships in improving teaching and learning and in facilitating educational change” (Moolenaar, 2012, p. 11). Using a social network approach to understand teachers' social capital provides a way to focus not only on the individual, but also on whole networks. Indeed, it is within the whole-school teacher community that individuals maintain the professional ties shaping their social capital (Penuel et al., 2009). Social capital is related to the resources embedded in teachers' professional relations and refers to the centrality of these teachers in the whole-school network (Berebitsky & Andrews-Larson, 2017). Consequently, social capital has often been considered in terms of teachers' degree centrality (Berebitsky & Andrews-Larson, 2017; Daly et al., 2020), because it operationalizes directly the number of colleagues in their professional network, or through teachers' closeness centrality, which operationalizes how easily the teachers can access their colleagues or how socially close teachers are to their colleagues (Hopkins, Bjorklund, & Spillane, 2019).

More and more researchers in educational sciences have adopted a social network perspective to study relational aspects of the teaching profession such as collaboration, distributed leadership, reform implementation, teacher induction, or teacher professional development (Moolenaar, 2012). As is the case from a social capital theoretical lens, the social network lens in the field of teacher professional development builds on the fundamental assumption that resources, information, tips, routines, and knowledge pass to the individuals through relationships (Moolenaar, 2012). Social networks are relevant both theoretically and methodologically speaking. Social network analysis enables scholars to understand what the relationship pattern between teachers is, how this pattern can be explained, and what the consequences are, and it is therefore a relevant way to grasp this pattern (Baker-Doyle & Yoon, 2020).

2.3. A social network perspective: methodological point of view

As stated in the introduction, in social network analysis, the network is itself a source of dependence of observations (Tranmer et al., 2014). As the network *is* the social fabric within a given environment (such as a clique of friends, a classroom, a subgroup of teachers, a school department, a whole organization, a country, etc.), it inherently carries a dependency between the network observations (Silk et al., 2017). This can be illustrated with an example on the transitivity of friendship. If individual i is a friend of individual j, and j is a friend of k, there is a good chance that i is a friend of k, too. If we are interested in individual data, also called attributes (such as the number of friend nominations), X_i, X_j, and X_k are not independent observations. It is the same scenario if we are interested in network dyadic data (such as the existence of a friendship tie between individuals), X_{ij}, X_{jk}, X_{ik} are not independent observations either (Snijders, 2011). In other words, social network observations are inter-correlated. This issue is well-known as “Galton's problem” (originally stated for the cultural dependence of data; Freeman, 2004). Consequently, most conventional statistical procedures and models cannot be used with network data, because such data violate the basic assumption of the independence of observations (Borgatti, Everett, & Johnson, 2018). This dependency issue can be related to the consequences of the network (effect of contagion), to the formation of the network (effect of reciprocity), or to the network data (effect of sample autocorrelation). We can subsume these elements by a fundamental idea: taking into account the entire network is necessary when exploring a phenomenon through social network approaches (Froehlich & Sarazin, Submitted).

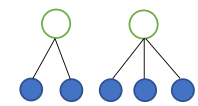
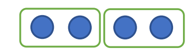
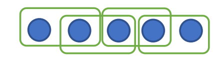
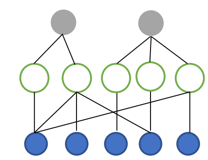
The social network literature has presented a range of statistical tests and procedures dealing with this issue of interdependence. Well-known statistical tools make it possible to predict the existence of ties according to nodal attributes (see exponential random graph models [ERGM] and P*1 P*2 models), to run correlations or regressions between networks (see quadratic assignment procedures [QAP]), and to predict network evolution (see stochastic actor-oriented models [SAOM]). Despite this growing emergence of statistical tools designed for social network analysis that deal with the issue of interdependence, procedures to predict individual continuous variables with network data are still quite unexplored. This gap might be surprising to the reader, but it can be understood in light of the history of social network analysis. Historically, social network analysis has emphasized the social structure of a given reality (Froehlich, Van Waes, & Schäfer, 2020), trying to analyze and explain the pattern of ties between actors in a network (Wellman, 1983). Social network analysis is fundamentally about the configurations of social relations (Scott, 2011). In this sense, the network is mainly the object of the analysis in social network analysis (as in the statistical procedures listed previously), while in this study, we want to use the network as a way to represent the reality through which our data emerge (i.e., use the network to predict individual outcomes).

This lack of an applicable statistical procedure has led scholars in teacher research to model the structural or relational aspects they are interrogating statistically without being completely able to capture them by using a regular multilevel model, which cannot control for the specific interdependence of social network observations (Berebitsky & Andrews-Larson, 2017; Daly et al., 2020; Edinger & Edinger, 2018; Moolenaar & Sleegers, 2010). Some of these researchers have acknowledged the dependence of their network data as a limitation, others have not.

To fill this gap, efforts have been made to transfer statistical models coming from other fields such as geographical literature, which uses models controlling the spatial dependence of observations, what is called an “autocorrelation model” (Tranmer et al., 2014). Table 1 presents different models that can be used to predict a continuous individual-level variable with network data while dealing with network data interdependence. We briefly explain these different models and enter into detail for the last one (i.e., MMMCM), as that is the one we build on for the statistical procedure used in this study.

A hierarchical linear model (HLM) is the classic multilevel model used with data nested in structures such as classrooms, schools, or organizations. In this model, each individual is nested in one and only one higher-level unit. For example, one teacher is nested in only one school. This is an often-used model that is relevant for taking the data interdependence and group influence into account, but that cannot handle situations where observations are nested in multiple clusters at the same level (Chung & Beretvas, 2012), such

Table 1
Models dealing with the dependence of observations.

Model	Basic functioning	Illustration
Hierarchical linear model (HLM)	"The exclusive group model" - Interdependence within the group - Individuals embedded in one group	
Actor-partnership influence model (APIM)	"The couple model" - Interdependence within an Actor-Partner dyad - Individuals embedded in one dyad	
(Temporal) Network autocorrelation model (TNAM)	"The neighborhoods model" - Interdependence between neighbors (can be indirect neighbors) - The neighborhood is the only possible level	
Multiple-membership multiple-classification model (MMMCM)	"The embeddedness model" - Interdependence between related individuals - Can be nested in other group levels	

as teachers who work in several different schools; this is a major gap in dealing with social network data. See Moolenaar and Sleegers (2010) and Daly et al. (2020) for examples of social network studies (teachers' professional network) in education using HLM.

An actor-partnership interdependence model (APIM; Cook & Kenny, 2005) is similar to an HLM, with the particularity that the nested structure is each pair making up an "actor-partner couple" (Hong & Kim, 2019). The fundamental idea is that observations in dyadic partnerships are interdependent (Fitzpatrick, Gareau, Lafontaine, & Gaudreau, 2016). In this type of model, an individual can be nested in one and only one dyadic group. See Zhou, Heather, Di Cesare, and Ryder (2017) for an example of a social network study (friendship dyads) in social psychology using APIM; we did not find any studies using this model specifically in education.

The (temporal) network autocorrelation model ([T]NAM; Leifeld, Cranmer, & Desmarais, 2018) is a model inspired by geographical literature (Tranmer et al., 2014). It allows implementation of temporal autocorrelation or spatial cross-sectional autocorrelation and, in this way, takes into account the interdependence of different observations of the same individual over time, or the interdependence of observations between "neighbors", connected observations (Mercken, Snijders, Steglich, Vartiainen, & de Vries, 2010). In (T)NAM, the neighborhood is the only possible level of clustering. See Vitale, Porzio, and Doreian (2016) for an example of a social network study (students' exchange network) in education using (T)NAM.

The multiple-membership multiple-classification model (Tranmer et al., 2014) could be defined as a combination between (T)NAM and HLM. It provides a way to take into account network data interdependence, with individuals nested in several networks, as well as other levels of interdependence (Tranmer et al., 2014). For example, a teacher is part of several groups of teachers (with his colleagues in the whole-school network) and part of a specific school. See Tranmer et al. (2014) for an example of a social network study (friendship network) using MMMCM. This model is particularly relevant regarding our purpose because it provides a way to cluster teachers into several small networks such as ego networks, dyads, triads, or larger cliques and also to nest teachers in their schools. In our opinion, this is the most complete model for when researchers want to assess the relations between social network data and a continuous individual variable while controlling for this issue of observation interdependence at different levels (tackling the autocorrelation dependence issue).

Whereas the study by Tranmer et al. (2014) is an interesting starting point, their friendship network was fundamentally different from our professional network. As an example, in their study, they decided to consider that the more friends an individual has, the less important his or her impact on these friends is. As a result, an individual with 4 friends will have a weight or a "membership coefficient" of ¼ in each ego network. Indeed, this was a subjective choice that was inspired by a fundamental article describing the MMMCM method (Browne, Goldstein, & Rasbash, 2001). In that article, the authors chose to weigh the membership in different illustrative situations using the coefficient 1/r, where r is the number of memberships for an individual. Yet, other weightings are possible, so that the choice of how to weight should depend on theoretical insights and/or model fit information (Durrant, Vassallo, & Smith, 2018). We exhaustively describe in the method sections the choices made in this study, to provide a transparent, replicable procedure for using data from teachers' professional networks. This procedure was inspired by Leckie's routine for preparing non-network data for use with the multiple-membership model (Leckie, 2013).

3. Method

3.1. Data collection and participants

Data collection was conducted in two secondary schools offering technical and vocational (TVET) programs in the French-speaking part of Belgium. We selected schools offering TVET programs because of their high proportion of SCTs. Data collection for the first school was done in February 2020 and for the second at the end of April 2021.[2]

Data were collected through a survey subdivided into three parts. The first part was related to biographical information such as years of experience and first or second career teacher status. The second part was a name generator (Borgatti et al., 2018) to obtain the complete professional network of the school (Tuytens, Moolenaar, Daly, & Devos, 2019). More specifically, we were interested in teachers' professional interactions as their available

[2] Because of the Covid-19 pandemic, we had to postpone the data collection for the second school, waiting until the situation for secondary schools returned to somewhat normal.

social capital, therefore we focused on identifying the colleagues with whom they talked about work. The name generator was the question, "Since September, to which colleagues do you turn to talk about work?" (Moolenaar & Sleegers, 2010). We asked the teachers to add the frequency of interactions, ranging from 1 to 5 (1 = *a few times a year*, 5 = *every day*). The third part was the teachers' work socialization scale, enabling us to operationalize to what extent they were socialized into the teaching job. Only teachers (FCTs and SCTs) were asked to complete the third part. Principals and school leaders only responded to the first and second parts of the survey. The response rate was 79% for the first school ($n = 104$) and 82% for the second ($n = 78$), which meets the requirement of 75% participation to generate whole network data (Kossinets, 2006).

3.2. Measures

Independent variables. Teachers' social capital was operationalized in two ways. First, it was operationalized with degree centrality, which is the number of colleagues with whom a teacher has professional interactions (both ingoing [indegree centrality] and outgoing professional interactions [outdegree centrality]). Degree centrality is a relevant way to operationalize social capital, because the more colleagues teachers have professional interactions with, the more resources they have to help them develop in the job (Borgatti, Jones, & Everett, 1998). This score was weighted by the frequency of interactions, ranging from 1 to 5 (1 = *a few times a year*, 5 = *every day*). Second, social capital was operationalized through closeness centrality. Closeness centrality represents how socially close a teacher is to all the other teachers in the professional network of the school. Closeness centrality is also considered as a way to operationalize social capital (Kovanovic, Joksimovic, Gasevic, & Hatala, 2014), because the greater a teacher's closeness is, the more opportunities he has for professional interactions (Liou et al., 2017). As an illustration of these centrality measures, in Fig. 2, Frank has the highest degree centrality and Rosa has the lowest closeness centrality. In order to neutralize the between-school differences, indegree, outdegree, degree centrality, and closeness centrality variables were standardized on the school mean.[3] We extracted these centrality measures from the whole-school network with Gephi software (Bastian, Heymann, & Jacomy, 2009).

Control variable. We controlled for years of experience in the teaching profession, as this can influence both work socialization and the number of professional interactions with colleagues. Years of experience are even sometimes considered as a proxy for human capital that could also act as a predictor of teachers' work socialization (see Daly et al., 2020). We did not standardize years of teaching experience. As such, the coefficient represents the effects of each additional year of teaching experience on teachers' work socialization.

Dependent variable. We used the ISaTE-scale (Teachers' work socialization scale; Coppe et al., 2020) to measure the work socialization of teachers. The scale, tested on a large sample in French-speaking Belgium (Coppe et al., 2020), has strong structural validity and strong measurement invariance between first and second career teachers, as well as between novice teachers ($\leq$5 years in teaching) and more experienced teachers (>5 years in teaching). The 20 items on the scale inquire about four aspects forming the global score for teachers' work socialization. The items use Likert-scale responses ranging from 1 (*I completely disagree*) to 5 (*I completely agree*). The first aspect is task socialization (example item: "I know how to explain the subject content to students so that they understand it"). The second aspect is group socialization (example item: "I am not usually present at informal meetings of colleagues [reverse-code]"). The third aspect is micropolitical climate socialization (example item: "I know who the most influential people are among my colleagues"). The fourth aspect is organization socialization (example item: "I think I fit well with my school"). The scale had a good reliability score (α = .84). ISaTE scores were standardized on the school mean, following the same logic as for the independent variables.

Group variable. As we were interested in differences between first and second career teachers in the importance of professional interactions, we used this status as a binary variable (1 = first career teacher; 2 = second career teacher). We defined second career teachers as teachers who had a prior professional occupation before being teachers (Trent, 2018), while for first career teachers, teaching was their first professional occupation.

Multilevel cluster variables. Each ego network was considered as a cluster, a regrouping of teachers in relation to the "owner" of the ego (see data preparation section). There were 104 and 78 clusters in the first and second school, respectively. Consequently, level 2 of the hierarchical structure was formed by 182 cluster variables, each being one ego network. Ego-network clustering was preferred to other social network clustering variables as dyad, triad, or n-clique. Ego networks showed better fit indices (Tranmer et al., 2014). Choosing ego networks to nest the observations in was also a more parsimonious choice, because ego networks represent one level of embeddedness, while dyad, triad, and so on, represent several hierarchical levels. As we added self-membership (one teacher is a member of their own ego network), our ego networks included part of the n-clique information.

3.3. Data preparation for the multiple-membership multiple-level social-network models

Multiple membership multiple classification social network models require specific data preparation to make the analysis possible (Leckie, 2013). We describe the different steps of the data preparation in this section, with a brief introduction to the encoding of social network data for the sake of clarity.

There are mainly two ways to encode social network data. The first takes the form of an adjacency list,[4] and the second takes the form of an adjacency matrix (Borgatti et al., 2018). An adjacency list, in its simplest form, presents one line per ego and for each ego, the list of the alters[5] (see Table 2 – unweighted). Weights for each alter, such as the frequency of the interactions, can be added to this simplest form (see Table 2 – weighted).

An adjacency matrix is the organization of this adjacency list in a matrix. Each person in the network is listed in the first row and the first column to obtain a N x N matrix (with N the number of individuals in the network). The cells in this matrix show a 0 if there are no ties between the individual in the row and the individual in the column, or 1 if there is a tie (see Table 3 – unweighted). This matrix can also present the weights of the ties, such as the frequency of interactions (see Table 3 – weighted). If the ties are considered to be directed (i.e., one-directional, such as asking for advice from someone), the matrix is asymmetrical. If the ties are considered to be undirected (i.e., two-directional, such as Facebook

[3] An alternative could be to standardize these data on the whole sample mean, if the researcher wanted to take into account differences between schools. With a larger number of schools, this would be the case if a three-level model was used, with schools at level 3.

[4] A third way could be an edge list, but we consider that to be an extended version of an adjacency list.

[5] The term alter refers to someone who is mentioned by an ego.

Table 2
Example of a hypothetical adjacency list.

Unweighted				
(ego 1) Frank	(alter 1) Mary		(alter 2) Evelyn	
(ego 2) Mary	(alter 1) Rosa		/	
(ego 3) Evelyn	(alter 1) Frank		(alter 2) Dominik	
(ego 4) Rosa	(alter 1) Evelyn		/	
(ego 5) Dominik	(alter 1) Frank		/	
Weighted				
Frank	Mary	3	Evelyn	2
Mary	Rosa	2	/	/
Evelyn	Frank	2	Dominik	4
Rosa	Evelyn	1	/	/
Dominik	Frank	2	/	/

Table 3
Example of a hypothetical asymmetrical adjacency matrix.

	Frank	Mary	Evelyn	Rosa	Dominik
Frank	0	1[3]	1[2]	0	0
Mary	0	0	0	1[2]	0
Evelyn	1[2]	0	0	0	1[4]
Rosa	0	0	1[1]	0	0
Dominik	1[2]	0	0	0	0

Note: Unweighted [Weighted].

friendship, which is automatically reciprocal), the matrix is symmetrical.

For the data preparation procedure used and explained in this study, the data must be in matrix form. Ucinet and R packages (igraph, sna) have routines to generate a (weighted) matrix on the basis of an adjacency list. In this study, the whole network matrix of professional interactions between teachers was an asymmetrical matrix weighted by the frequency of interactions (similar to the matrix presented in Table 3 [Weighted]). This matrix was the social network material we used for the next steps.

Social network observations are interdependent because of the relations between individuals; therefore, we needed to model this dependence in clusters of relations. Inside each cluster, observations share autocorrelations between them. The following explanations were inspired by a combination of the procedure described by Tranmer et al. (2014) for friendship network dependence and the procedure described by Leckie (2013) for non-network multiple-membership data. The most intuitive way to nest individuals in relationship clusters is to consider that each individual has a personal network (so-called an ego network), and other individuals in the whole network can be part of (or nested in) someone else's ego network. In this way, for every individual *i*, all of the people who are connected with *i* are nested in the ego network of individual *i*. To do this nesting, we needed to transform the asymmetrical weighted matrix into a symmetrical weighted matrix (see Table 4), because the purpose was to cluster teachers together if they have professional interactions (whether ingoing or outgoing). Additionally, we added the information that teachers are part of their own ego network by filling the diagonal with the number 5, representing the highest membership weight.

This new symmetrical weighted matrix could be directly used as the data table indicating the individual's memberships in the different ego networks and could be imported into our final data table. These memberships were not exclusive to one ego network and represented level 2 of the multiple-membership social-network model that we used in this study (see Fig. 1 for an illustration of the multilevel structure of our hypothetical example and Fig. 2 for an illustration of the embeddedness of ego clusters in the small whole network corresponding to our hypothetical example). This model enables to consider the autocorrelations between observations in a random intercept for each ego cluster. In our final data table, each row represents an individual and each column one cluster (Frank's ego network, Mary's ego network, etc.). In this table, other variables such as predictors, outcomes, or other clustering variables (such as teachers' school membership) can be added. An illustration of the final data table used for this study is presented in Table 5.

Table 4
Example of a hypothetical symmetrical weighted adjacency matrix with diagonal filled with 5.

	Frank	Mary	Evelyn	Rosa	Dominik
Frank	5	3	2	0	2
Mary	3	5	0	2	0
Evelyn	2	0	5	1	4
Rosa	0	2	1	5	0
Dominik	2	0	4	0	5

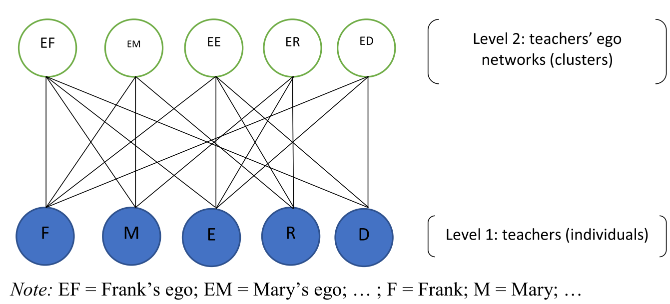


Fig. 1. Multiple-membership multilevel structures
Note: EF = Frank's ego; EM = Mary's ego; …; F = Frank; M = Mary; ….

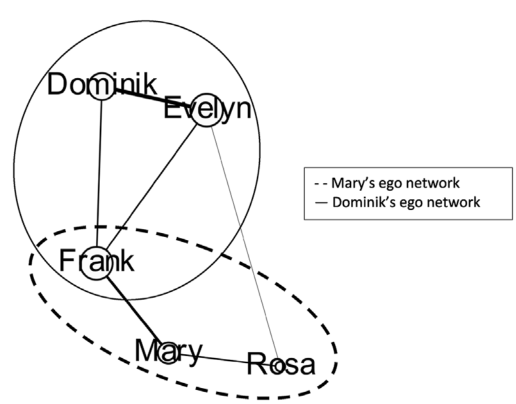


Fig. 2. *The embeddedness of ego networks, as illustrated by Mary's and Dominik's ego networks.*

Table 5
Illustration of the format of the data table used in this study (simulated data).

	FCT/SCT	Years	DC	CC	WoSo	Ego F.	Ego M.	Ego E.	Ego R	Ego D.
Frank	1	5	1.40	0.30	0.81	5	3	2	0	2
Mary	2	12	−0.97	−0.53	0.28	3	5	0	2	0
Evelyn	2	7	−1.02	−0.30	−0.82	3	0	5	1	4
Rosa	1	6	0.11	−0.68	0.25	0	3	1	5	0
Dominik	1	18	0.60	0.32	1.24	2	0	4	0	5

Note: FCT = first career teachers (1)/SCT = second career teachers (2); Years = years in the teaching profession; DC: z-score for degree centrality; CC = z-score for closeness centrality; WoSo = z-score for work socialization.

3.4. Data analysis

We passed through different analytic steps to answer our research questions. The analyses explained in this section were conducted in Stata 16.1. The model fits were compared using AIC and BIC criteria (Müller, Scealy, & Welsh, 2013). We used the REML estimator because of the relatively small size of our sample (McNeish, 2017). As a preamble, we ran a null model (without any predictors) to compare the relevance of this MMMCSNA to that of a linear model.[6] Additionally, as an illustration of this relevance, we presented a comparison between MMMCSNA and regular linear models for some of the selected fitted models at the end of the results section.

For the first research question, we added our different predictors to the model step-by-step. We ran different models for weighted indegree and weighted outdegree centrality, because of the conceptual and empirical correlation between them ($r = .44$, $p < .001$). We also ran different models for weighted degree centrality and closeness centrality, because they are two different ways to operationalize social capital. For the second research question, we reused the final models obtained for the first research question (on the basis of AIC and BIC) and tan these models for first and second career teachers.[7] In all of these models, ego networks were considered at level 2. As our research questions focused on the individual level, we treated the structural effect (teachers nested in ego networks) as a nuisance, that is, as the network data dependence we had to control for. Consequently, we focused our interpretation on the level 1 variance in the model.[8] Our model worked as a multi-level model with two levels. Thus, it captured from the singularity of each cluster to what extent the variability in the dependent variable was related to the variability in the independent variables.

4. Results

The null model[9] showed the relevance of our MMMCSNA model compared to a linear model ($\chi bar^2_{0,\ 1} = 6.54$; $p < .01$), which demonstrated a significantly better fit than the single-level linear model. At the end of the results section, we have compared some of the fitted models using MMMCSNA and regular linear models to highlight the differences.

Table 6 presents the results for models 1, 2, 3, and 4, which addressed the first research question. First, in model 1, we entered weighted indegree centrality as a predictor of work socialization. In model 1a, we added years of teaching as a second predictor. Model 1a presented a better fit than model 1, with lower AIC and BIC values. Model 1a showed that weighted indegree centrality predicted the work socialization of teachers ($\beta = 0.27$; $p < .001$). This means that ingoing interactions had an impact on the work socialization of teachers. This model also showed that years of teaching experience predicted teachers' work socialization. For each additional year of experience, teachers' work socialization score was 0.02 standard deviations higher ($B = 0.02$; $p < .001$).

Second, in model 2, we entered weighted outdegree centrality as a predictor of work socialization. In model 2a, we added years of teaching as a second predictor. As with the first models, model 2a presented a better fit than model 2, with lower AIC and BIC values. This model showed that weighted outdegree centrality significantly predicted the work socialization of teachers ($\beta = 0.27$; $p < .001$), meaning that outgoing professional interactions had the same impact on teachers' socialization as ingoing professional interactions. The equivalence of the two standardized coefficients ($\beta = 0.27$; $p < .01$) can be interpreted as an equivalent influence of these two directionalities of their professional interactions on teachers' work socialization. This model showed the same result as the previous one regarding the impact of years of teaching experience on teachers' work socialization.

As weighted indegree and outdegree centrality were both significant, in model 3 we entered the combination of them, resulting in weighted degree centrality as a measure of social capital, alongside years of teaching experience. Model 3 showed that weighted degree centrality significantly predicted teachers' work socialization ($\beta = 0.40$; $p < .001$) with a high standardized coefficient, meaning that social capital had a strong impact on teachers' work socialization. In this model, years of experience had the same impact as in model 1a and 2a ($B = 0.02$; $p < .001$).

Fourth, in model 4 we tested the predictive effect of closeness centrality as our second operationalization of social capital. Model 4 showed that closeness centrality significantly predicted the work socialization of teachers, but with a smaller standardized coefficient that weighted degree centrality ($\beta = 0.29$; $p < .05$). In this model, years of teaching experience also significantly predicted work socialization ($B = 0.03$; $p < .001$).

Tables 7 and 8 address our second research question. Table 7 presents standardized means for the variables of interest for first and second career teachers. SCTs had smaller standardized means for all of these variables.

Table 8 presents the results for several models. In model 5, we entered weighted degree centrality and years of experience as independent variables and teachers' work socialization as the dependent variable. This model was run separately for first career teachers (model 5) and second career teachers (model 5a). Models 5 and 5a showed that weighted degree significantly predicted teachers' work socialization for both first and second career teachers, but with a much higher standardized coefficient for

[6] This model control only for the interdependence of observation inside the ego networks for the dependent variable. See the comparison between MMMCSNA and single-level regression models to see the impact of controlling both for interdependences in the independents and dependent variables.

[7] We ran different model for FCTs and SCTs instead of using this binary variable as a moderator. FCTs interacted mainly with FCTs and SCTs interacted mainly with SCTs (logic of homophily). Consequently, our level 2 variable captured a large part of the variance related to the status of FCT or SCT, making it irrelevant to enter the status in the model.

[8] To interpret the level 2 variance in MMSNA, see Tranmer et al. (2014).

[9] Model with teachers' work socialization only.

Table 6
Multilevel model estimates — dependent variables: Teachers' work socialization.

	Model 1 ($n = 147$)		Model 1 bis ($n = 142$)		Model 2 ($n = 147$)		Model 2 bis ($n = 142$)		Model 3 ($n = 142$)		Model 4 ($n = 142$)	
	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.
Weight. Indegree	0.33**	0.10	0.27**	0.09					–	–	–	–
Weigh. Outdegree					0.31***	0.08	0.27**	0.08	–	–	–	–
Weight. Degree	–	–			–	–			0.40***	0.10	–	–
Closeness	–	–			–	–			–	–	0.29*	0.12
Years of exp.[a]	–	–	0.02**	0.01			0.02**	0.01	0.02**[1]	0.01	0.03***	0.01
AIC	415.12		398.32		414.18		397.20		391.86		399.72	
BIC	427.08		413.10		426.15		411.98		406.54		414.50	

Note: * < 0.05; ** <0.01; *** >0.001.
[a] Coefficient for the year of experience is not standardized.

Table 7
Standardized means FCTs and SCTs by schools.

	FCTs ($n = 83$)	SCTs ($n = 64$)
Work socialization	0.11	−0.13
Weighted degree centrality	0.05	−0.12
Closeness centrality	0.07	−0.10

Table 8
Multilevel model estimates (FCTs/SCTs) predicting teachers' work socialization.

	Model 5 (FCTs) ($n = 81$)		Model 5a (SCTs) ($n = 61$)		Model 6 (FCTs) ($n = 81$)		Model 6a (SCTs) ($n = 61$)	
	β	SE	β	SE	β	SE	β	SE
Weighted Degree	0.33**	0.11	0.54**	0.18	–	–	–	–
Closeness	–	–	–	–	0.13	0.15	0.48**	0.18
Years of exp.[a]	0.02**	0.01	0.01	0.01	0.02**	0.01	0.02	0.01
AIC	218.21		189.31		223.76		191.32	
BIC	230.19		199.87		235.73		201.87	

Note: * < 0.05; ** <0.01; *** >0.001 FCTs = first career teachers SCTs = second career teachers.
[a] The coefficient for years of experience is not standardized.

second career teachers. Years of teaching was a significant predictor for first career teachers, but not for second career teachers.

Second, we entered closeness centrality and years of experience as independent variables and teachers' work socialization as the dependent variable. This model was run separately for first career teachers (model 6) and second career teachers (model 6a). Models 6 and 6a showed that closeness centrality significantly predicted teachers' work socialization only for second career teachers. The standardized coefficient for closeness centrality was close to the standardized coefficient for weighted degree centrality in the case of second career teachers. Years of teaching was significant for first career teachers, but not for second career teachers.

To end this results section and as an evaluation of our second objective, Table 9 presents a comparison between the estimates from our MMSNA and regular linear regression for the last models presented (models 5, 5a, 6, and 6a). This comparison showed similar results and interpretations for some of the estimates, but showed important differences, too[10]. Using linear regression would have led to interpretation errors regarding the coefficient and the significance of closeness centrality in Model 6. Overall, linear regression seemed to increase the value and significance of the coefficients compared to MMSNA, leading to some possible misinterpretations.

5. Discussion

Following the nature of our two main objectives, this discussion presents first, the theoretical implications, second, the methodological implications. Then, we propose the limitations and practical implications of this study.

5.1. Theoretical implications

First, our results clearly show the importance of social capital for teachers' work socialization. This is in line with current trends in the literature presenting the importance of peers for developing in the teaching job (Baker-Doyle & Yoon, 2020; Colognesi et al., 2020; Moolenaar, 2012; Penuel, Sun, Frank, & Alix Gallagher, 2012; Thomas et al., 2020). The number of professional interactions proved to be a strong predictor of teachers' work socialization. This confirms that the more teachers have work-related discussions, the more they evolve professionally (Daly et al., 2020; Grangeat & Gray, 2007; López Solé, Civís Zaragoza, & Molina González, 2018). Results were less clear when operationalizing social capital through closeness centrality. For first career teachers, closeness centrality did not significantly predict work socialization. The relation was positive though. We could postulate that because they have enough direct interactions to fulfill their needs, they do not need central positions to give them easy access to colleagues reachable through other 'more direct' colleagues (i.e., to indirect colleagues).

Second, this importance of social capital is more significant for second career teachers. The impact of professional interactions was stronger for second career teachers than for first career teachers. Similarly, the ease of access to colleagues for professional interactions was only significant for second career teachers. This confirms previous studies stating that collegial dynamics are of extra importance for second career teachers (Csíkos et al., 2018; Lee, 2011). It also shows that being in the periphery of the network (i.e., being socially distant from colleagues) has a negative impact on the work socialization process. Following Perez-Roux and Lanéelle (2013), we can postulate that because of the fast alternative certification program they pass through, or the absence of pedagogical certification, their work socialization process is mainly an "on-the-job" workplace learning process that requires professional interactions and collegial dynamics around them. SCTs benefit from access to direct colleagues as well as easy access to indirect colleagues in order to develop as teachers.

Third, given this significance of social capital for the work socialization of second career teachers, descriptive statistics (see Table 7) that identify them as having lower social capital scores and

[10] The same picture was seen for the other MMSNM reported in the results section.

Table 9
Comparison of MMMCSNA and regular linear model estimates.

	MMMCSNA				Regular linear model			
	5	5a	6	6a	5	5a	6	6a
	β	β	β	β	β	β	β	β
Weighted Degree	0.33**	0.54**	–	–	0.39***	0.54**	–	
Closeness	–	–	0.13	0.48*	–	–	0.29*	0.48**
Years of exp.[a]	0.02**	0.01	0.02**	0.02	0.02**	0.01	0.03**	0.02

Note: * < 0.05; ** < 0.01; *** <0.001.
[a] The coefficient for years of experience is not standardized.

subsequent lower work socialization scores must open our eyes to this critical situation. Our results confirm that second career teachers are more isolated than first career teachers (Coppe, März, & Raemdonck, 2021) and they highlight how this situation can have a negative impact on their work socialization. To emphasize once again the importance of social capital for SCTs and teachers in general, we would like to join our voice with Newberry and Allsop who claim that:

> (…) that is not necessarily the challenges of the field, nor the characteristics of the individual that determine if one stays or leaves; it is the structure of the social-professional support (…). With adequate support through collegial relationships that are personally and professionally significant, we believe that many more teachers may be able to enjoy a longer, more successful teaching career. And in the end, that is a benefit to the schools and children alike" (2017, p. 876–877).

5.2. Methodological implications

This paper provides a transparent and replicable methodology to use social network data as a predictor of continuous individual outcomes. By doing so, we hope to reduce the existing gap in the social-network literature regarding the lack of statistical procedures for using social network data as predictors of individual outcomes. The methodological procedure we presented enables researchers to explore socially-embedded phenomena (such as teacher development) while considering the entire network in which they take place. As such, by nesting teachers in teachers' ego networks for the whole school, we were able to control for the dependence of network observations. As this model follows the multilevel model mechanisms, it also accommodates the nesting of teachers in schools and of schools in macro-systems. Again, these levels 3 and 4 could take into account a multiple membership situation (e.g., teachers working in several different schools).

As shown by comparison between estimates in the MMSNA model and single-level regression model, the single-level regression model seemed to increase the value and significance of the coefficients. Thus, considering the dependence of observations at the level of the ego networks made it possible to avoid misinterpretations and type I errors.

5.3. Limitations

Certain limitations must be kept in mind regarding this study. First, we aimed to tackle the autocorrelation dependence between network observations. We were not interested in controlling for other types of dependence such as the contagion effect or reciprocity effects, which are related to other research questions than those addressed in this study. For example, we did not try to "explain" the formation of the network, we just took it as a given. Second, the model presented called for entering the school at level 3. As our sample included only two schools, we were not able to consider level 3. Increasing the sample size would make it possible to enter the school at level 3 and to refine the results highlighted in this study. Third, we attributed the maximum membership-weight to teachers for their own ego network, which makes sense theoretically but could be arguable. Indeed, even if teachers are the center of their own ego network as each teacher of this small network is connected to them, they do not necessarily play the most central role in their ego-network. Fourth, because of the homophily issue we described in the data analysis section,[11] we ran separate models for first and second career teachers. Therefore, we were unable to report inferential tests to support the generalization of the differences we found between these two subgroups of teachers. Fifth, it should be noted that the variable "years of experience" could be constructed to take into account not only seniority in the profession (which is what we did), but also seniority in the school currently attended. Given the way we worked with the concept of teachers' work socialization, such a variable could have a distinct pattern from seniority in the profession. Sixth, in our measures of social capital we weighted the ties with their frequencies. Using frequencies of ties is one way to measure the 'strength' of the relationships. However, we could also have measured the quality of ties (Siciliano, 2016). In addition, to generate our measure of closeness centrality, we could have weighted the ties by a measure of subjective perceived closeness (Lee & Bonk, 2016) instead of frequency. It would have directly weighted the ties by teachers' perception about the ease of access to colleagues in their networks. In this study, the measure of closeness centrality takes into account only the structural distance (based on frequencies) between a node and the other nodes of the whole network. Finally, although schools in French-speaking Belgium were functioning relatively normally during our data collection in school 2, the context of the COVID-19 crisis was still present. This context may have impacted the day-to-day work of teachers, and our results should be considered carefully for their possible generalizability.

5.4. Practical implication

To open the school doors to more and more second career teachers requires taking the time to think about their work socialization process in order to keep them in the profession. In this study, we showed that a key factor in this process is the availability of social capital through interactions with peers. As noted by Rose and Sughrue (2020), school principals may not be aware of the importance of social capital for meeting the specific needs of

[11] i.e., FCTs interacted mainly with FCTs and SCTs interacted mainly with SCTs (of homophily according to career type). Consequently, our level 2 variable captured a large part of the variance related to the status of FCT or SCT, making it irrelevant to enter the status in the model, and necessary to run two different models.

second career teachers. Because second career teachers develop their competencies and familiarize themselves with the job mainly "on the job" (Perez-Roux & Lanéelle, 2013), the responsibility to support their work socialization falls on the school (Rose & Sughrue, 2020). Yet, second career teachers do not receive special "on-the-job" training or support (OECD, 2021), which represents a major issue to address. More generally, given the importance of building strong social capital for both first and second career teachers, principals could turn to distributed mentorship practices. Through the measure of closeness centrality, representing the ease of access to indirect colleagues, our results showed that the peripheral positions held by second career teachers in their school professional networks can have particularly negative effects on their work socialization process. As shown in a previous study (Coppe et al., submitted), having few opportunities to ask and to share during work-related discussions represents a substantive problem for second career teachers' professional development.

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