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Longitudinal social network methods for the educational and psychological sciences

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ABSTRACT

Social network analysis is useful for obtaining a better understanding of antecedents and mechanisms of relationship formation and interactions between individuals in educational and psychological contexts. Research utilising descriptive and cross-sectional applications of network analysis is regularly reported, but longitudinal analyses of networks have received less scrutiny. In this methodological article, we compare three commonly applied approaches for analysing longitudinal social network data: Multiple Regression Quadratic Assignment Procedure (MRQAP), Separable Temporal Exponential Random Graph Models (STERGM), and Stochastic Actor Oriented Modelling (SAOM) with research questions about correlations, social structures and mechanisms, respectively. We highlight advantages and disadvantages of the methods and illustrate differences between these methods by analysing longitudinal peer-communication network data of pre-service teachers. The key considerations by the researcher are summarised as ‘FACTS’ (Focus, Assumptions, Conceptualisation, Time points, and Size) as an aid to researchers in selecting the most appropriate method for the analysis of longitudinal social network data.

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Introduction

In recent decades, social network research has gained prominence due to the growing recognition of the importance of including social context in research, the ability to collect comprehensive network data, and the availability of sophisticated social network analysis (SNA) methods within the fields of education and psychology (Mishra, 2020; Li et al., 2021). A social network is typically defined as a set of relationships or ties between members of a group, often referred to as actors. These actors, which may include individuals or organisations, are represented as nodes in a graph, with the connections between them depicted as ties. Each actor possesses certain characteristics, such as gender, age, or motivations, collectively known as attributes. SNA techniques are employed to study both the actors and their attributes within the network (Wasserman & Faust, 1994). Freeman (2014) identifies four key properties that characterise SNA as a distinct approach: (1) It involves the intuition that links among social actors are important. (2) It is based on the data collection and analysis that records connections among actors. (3) Graphic imagery can display patterns in those

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links. (4) It develops mathematical and computational models to describe and explain those patterns.

Analysis of network data requires different computational models. Conventional statistical methods, such as Ordinary Least Squares (OLS) regression, assume independence of observations. Social network data violates this assumption due to the interdependent nature of social ties between the actors in the network (Brouwer & de Matos Fernandes, 2023; Sweet, 2016). Some studies have employed conventional statistical methods, such as Hierarchical Generalized Linear Models (HGLM), to account for interdependencies in networks (Ennett et al., 2006; Meredith et al., 2020), but these are not specifically tailored to social network analysis. Longitudinal social network analysis techniques, such as Stochastic Actor-Oriented Models (SAOM; Snijders et al., 2010), are more appropriate for investigating social network mechanisms and patterns over time instead of investigating the variation in the outcome variable and taking into account the interdependent nature of the data as well as the social network structure.

Despite the availability of several tutorials and introductions to SNA (e.g. Kalish, 2020), researchers can feel overwhelmed by the variety of techniques and tools available for answering their research questions. Research in psychology and education indicates that researchers often limit their analyses to visualizations, descriptive social network statistics (e.g. centrality measures), or merely associations between attributes and network characteristics, thereby overlook the dynamics of social networks (Baker-Doyle & Yoon, 2011; Bokhove, 2018; Mishra, 2020; Sabot et al., 2017). In order to advance our theoretical understanding and provide temporal, causal explanations of dynamic social contexts and their underlying social network mechanisms, we require statistical techniques appropriate for analysing longitudinal whole-network data (Li et al., 2021).

Sweet (2016) discussed a range of descriptive measures (e.g. betweenness and closeness centrality) and methods tailored for SNA, such as ERGMs, and commonly applied in social sciences. While she acknowledges the advances in modelling longitudinal social networks, her valuable contribution to the literature does not cover a detailed discussion of the analysis of longitudinal social network data. This paper follows Sweet's (2016) lead in highlighting the affordances of SNA methods for educational and psychological sciences, while also addressing specific considerations for conducting social network analyses of longitudinal social network data. Some previous studies have compared longitudinal SNA methods. Ragan et al. (2019) applied both conventional linear modelling approaches and the SAOM approach to analyse longitudinal data from school-community-university partnerships. Robins et al. (2012) compared Quadratic Assignment Procedures (QAP), Exponential Random Graph Models (ERGMs), and SAOMs, although their study prioritised non-longitudinal ERGMs. Goldenberg et al. (2010) reviewed a range of models and proposed a categorization of statistical network models. However, none of these studies reviewed both the theoretical underpinnings of commonly used methods and applied them to the same dataset to illustrate the differences between the models and provide practical insights. Although recent literature provides guidance on conducting social network studies and highlights the value of longitudinally collected social networks (Broda et al., 2023; Brouwer & Froehlich, 2023; Gilman et al., 2022), two critical challenges remain. Firstly, determining the analysis techniques most suitable for a specific research question. Secondly, understanding the data requirements, advantages and disadvantages of each method for longitudinal SNA.

This paper focuses on three commonly applied statistical techniques for analysing longitudinal social network data in the social sciences, including the fields of education and psychology: the Multiple Regression Quadratic Assignment Procedure (MRQAP; Dekker et al., 2007), Separable Temporal Exponential Random Graph Models (STERGM; Krivitsky & Handcock, 2013), and Stochastic Actor-Oriented Modelling (SAOM; Snijders, 1996). MRQAP is included because despite it not being a dedicated longitudinal network approach, it has been popular among network researchers.¹ The other two methods can be situated under the dynamic variants of P1 models (Holland & Leinhardt, 1981), and they have been used in prior research by the authors. To improve

the reach of our work, we also required the methods to have up-to-date, open-source implementations of the methods. See Figure S1 in the supplemental materials to situate the three chosen methods.

MRQAP is a regression technique designed to account for the interdependence of social network data, but it has been used by Rienties and Nolan (2014) in a longitudinal study of cultural background as a predictor of how friendship and learning networks develop between international and host-country students. By contrast, STERGM (Krivitsky & Handcock, 2013) and SAOMs (Snijders, 1996) are specifically designed for the analysis of longitudinal social network data, offering deeper insights into the dynamics and changes in social network structures and their associated attributes. Bjorklund and Daly (2021) employed STERGMs to examine the structure of pre-service teachers' networks. The SAOM technique has been increasingly applied to study the dynamic social mechanisms of selection and influence, for example, the impact of students' grades on the development of their networks (Brouwer & Engels, 2021; Brouwer et al., 2022; Lomi et al., 2011). Other studies include dynamic processes underlying within-school friendship ties, smoking cessation, music tastes, alcohol consumption, and bullying (Geven et al., 2013; Sentse et al., 2013; Steglich et al., 2006).

The aim of this paper is to provide guidance in the identification of the three selected and commonly used methods for specific research questions in longitudinal social network designs by outlining the data requirements, assumptions, advantages and disadvantages of these methods. After a review and comparison of the three methods, we illustrate their differences using longitudinal communication network data from pre-service teachers (Brouwer et al., 2020). We suggest that the development of their support networks serves as an illustrative example of how longitudinal social networks and their underlying mechanisms, such as homophily (McPherson et al., 2021), can evolve in other settings. Additionally, the underlying data, research design, and research questions are applicable to all three selected methods. The overview and comparison of the three methods will assist researchers in selecting the most appropriate approach for analysing longitudinal social network data. Researchers should consider the requirements for data collection and design decisions, while also evaluating the strengths and limitations of each method at the start of a study. Importantly, the method selected should align with the specific research questions at hand. Selecting the most suitable method early in the research process is crucial, as it directly influences the quality of the research outcomes. As can be derived from supplementary Figure S1, we acknowledge that we are far from complete in our description of these longitudinal social analysis techniques, but we hope this helps the readers who want to apply MRQAP, STERGMs, or SAOMs.

Comparing MRQAP, STERGM and SAOM

Longitudinally collected social network data is often analysed using separate MRQAPs. The original QAP procedure, first proposed by Hubert (1987) and Mantel (1967), is a classic method used to assess bivariate associations between two networks. QAP can be extended to a more complex version known as MRQAP, which estimates regression coefficients similarly to standard (logistic) regression methods. Dekker et al. (2007) introduced a new permutation approach for QAP called 'double semipartialling' (DSP), which has become one of the most robust methods and is widely used for analysing longitudinal network data. MRQAP models can be applied to longitudinal network data since they examine the extent to which the whole network structure at a prior time point is predictive of the whole network structure at a later point in time. With MRQAPs, researchers can test whether covariates are associated with the network. MRQAP is useful if the focus is not network structure, but on the linear relation between independent and dyadic dependent variables in a network setting, while taking into account the interdependency of the network data (Krackhardt, 1988).

The major advantage of MRQAP is its simplicity in interpreting output as a normal simple regression. The effect of external (exogenous) covariates from various attribute data known on each

network actor can be modelled by producing a matrix of dyadic characteristics such as difference in group affiliation between members of the dyad or the sum of interpersonal trust between members of the dyad. MRQAP has several disadvantages. First, QAP approaches cannot model the complex structures within networks, since the very permutation methods used to address the interdependent nature of network data in QAP, condition out these structural characteristics from the model. Second, QAP approaches do not explain how factors influence the processes of tie formation and tie dissolution, i.e. network development over time. Third, in QAP analysis covariates (e.g. attributes) must be transformed into matrices and so the interpretation of these results can be challenging. Finally, MRQAP is not based on an underpinning theoretical model of network dependencies (Cranmer et al., 2017), and so precludes any opportunity to learn about and test the models underlying social network patterns or mechanisms.

Exponential Random Graph Models (ERGMs), also known as p^* -models, are statistical models specifically designed to analyse social network data (Harris, 2014). Initially, ERGMs were applied to cross-sectional data (Frank & Strauss, 1986; Lusher et al., 2013; Wasserman & Pattison, 1996). These models also allow us to account for both endogenous structural effects (e.g. reciprocity) and exogenous individual attributes that influence tie formation and dissolution within a time step (Lusher & Robins, 2013). *Separable* Temporal ERGMs (STERGMs) extend ERGMs in such a way that dynamic networks over discrete time intervals can be analysed (Krivitsky & Handcock, 2013). Unlike ERGMs, which provide a single model for the presence of ties in a cross-sectional network, STERGMs use two models to capture tie dynamics in a network over time: one for tie formation and another for tie dissolution. With STERGMs, researchers can test whether certain configurations (such as reciprocity, transitivity) would occur more often than we would expect by chance, enabling us to make inferences about tie patterns in the network. STERGMs, like all ERGM models, require the endogenous, structural characteristics of the network to be modelled and are tie-oriented (Block et al., 2019). An advantage of STERGMs is the possibility to model many of the structural factors which influence network development over time. There is a very wide range of structural factors that can be modelled in STERGM models, including and going beyond the basic dyadic and triadic structures related to reciprocity and transitivity and forms of closure (Krivitsky & Handcock, 2013). The breadth of variables that may be modelled will likely be key to research questions posed by those undertaking inferential network analysis, as these structural factors result from the interdependencies that exist between network actors and often lay at the heart of understanding network change.

STERGMs have several disadvantages. First, models are easily mis-specified when key factors are not included in the model and as a consequence, fitting models to the data can be difficult. A key challenge for the researcher is to select appropriate structural factors in a theoretically informed way. If researchers are more interested in variables other than those related to the endogenous network structure, then this can lead to challenges in specifying a model which will produce stable outputs. Second, estimating STERGMs can be computationally intensive, especially for large networks. While cross-sectional ERGMs are usually estimated using maximum likelihood methods (MLE), this can be problematic for estimating more complex longitudinal models with more included effects. The efficiency of model estimation procedures can be increased using pseudolikelihood processes (MPLE), but this in turn can lead to underestimating parameters used to determine confidence intervals, leading to incorrect statistical inferences (Cranmer et al., 2017).

Stochastic Actor-Oriented Models (SAOMs) are particularly effective at modelling network co-evolution (Snijders, 2001, 2005, 2010), such as how changes in networks co-evolve with changes in actor attributes over time. SAOMs are actor-based, which means that an actor 'decides' to maintain (endowment), create or dissolve a tie. The commonly used estimation procedure in SAOMs is the Method of Moments, which compares the expected parameter values derived from model statistics to the observed values. These values are obtained stochastically through an iterative process (Niezink, 2018; Niezink & Snijders, 2017; Snijders, 2001, 2005). As a continuous-time model, SAOMs allow for the analysis of longitudinal whole-network data, enabling researchers to test

hypotheses related to selection effects (e.g. homophily, popularity, activity related to an attribute) and influence effects (e.g. whether individual grades are influenced by the average grades of the friendship network).

An advantage of SAOMs is that they are well-suited for disentangling selection and influence (Snijders et al., 2007, 2010). Selection relates to tie change as one actor preferentially selects another for contact, for example, establishing a tie based on similarities or homophily, whereas influence relates to attribute changes as actors become more similar over time as a result of their ties (e.g. Steglich et al., 2012). To be informed whether homophily plays a role in selection of friends or that friends become similar over time, we need complete or whole networks with a fixed boundary within a range of 20 to 400 actors, e.g. classroom or department. Information about non-selection is necessary to understand whether selection takes place based on certain attributes (Steglich et al., 2012; Veenstra & Steglich, 2012). Similar to the aforementioned methods, parameter (effects) significance is tested by dividing the parameter estimate by the standard error, with absolute values greater than or equal to 2 indicating significance (i.e. the absolute value ≥ 2 is significant² (Ripley et al., 2024).

The SAOM approach has several disadvantages. First, estimation using SAOMs assumes gradual change in the network, so a large number of relatively rapid changes can be problematic (Snijders et al., 2010), as well as a response rate below 80%. Second, SAOMs are less suited for predicting rare events such as the creation of new ties in a sparse network (Block et al., 2018) and it can only model adjacent time points as one period without modelling the first time point itself (Snijders et al., 2010). Third, it can be particularly challenging for researchers to define the network boundary in SAOMs. The whole network data approach requires a definition of a network boundary, for example, a school class. Respondents can only nominate others within this network boundary, e.g. classmates (e.g. Laumann et al., 1983). Table 1 presents an overview and comparison of the three data analytic approaches.

Illustration in pre-service teacher networks

We illustrate the three different methods with data from a single cohort of mathematics pre-service trainees ($N = 37$) of the secondary Initial Teacher Education (ITE) program at a university in the south of England, for whom we measured peer support, communication network data, and collected attributes (Bokhove & Downey, 2018; Brouwer et al., 2020). Permission for the data collection was sought and given by the university ethics board of the first author (id 7675). Participants provided informed consent to participation and using their data. However, at the time of data collection, we did not ask explicit permission to publicly publish the data. We therefore provide a simulated dataset to explore the provided R code via https://osf.io/6dz8c/?view_only=bb0abdc4f77448ae8d96f59afb1be5e. The Supplemental Materials include a description of the raw data files.

Instruments and variables

Trainees were presented with names from their subject peer-group and asked whether they had any communication with this trainee during the last month. A positive response to this question would lead to participants being asked to indicate to which students they had turned for different types of support during the same time-period, including support with developing teaching strategies. Participants were also asked which of their peers they considered to be a personal friend. We refer to M1, M2, M3 and M4 as the data for the full (i.e. complete or whole) network for the mathematics trainees for time points 1, 2, 3 and 4 from this point onwards.

The dataset also includes two scale-based *actor attributes*. The scale for interpersonal *trust* includes items such as 'Even in difficult situations, I can depend on my fellow trainees', 'I find that my fellow trainees are open to me' and 'I also share personal information with my fellow trainees'

Table 1. Comparing the three methodological approaches MRQAP, STERGM, SAOM.

Approach	MRQAP	STERGM	SAOM
Research questions	• The probability that a certain network structure occurs due to covariates/predictors, which could include the network structure at an earlier time point. • e.g., How does X relate to Y (network)?	• The probability that a certain network structure occurs due to processes, such as reciprocity, transitivity, homophily, or an interaction of these. Longitudinal analyses are modelled as a consequence of changes in these processes. • E.g., How do network structures develop over time and how are these related to X? • Modelling of local tie-based configurations; 'tie-oriented' modelling. • Explaining the structure of a network (Block et al., 2018).	• The probability of network change in terms of endogenous network structures, exogenous dyadic attributes, actor attributes. • E.g., How do selection and influence mechanisms play a role in a network?
When and why?	• Modelling social network structures and attributes (covariates, predictors).		• Modelling selection on network change, separating influence from selection. • Explaining the mechanism of network evolution (change) by means of endogenous network structures (Block et al., 2018).
Characteristics	• Whole network structure at a prior timepoint is predictive of the whole network structure at a later time point. • Interdependent cross-sectional data. • Matrices should be created of attributes (similarity, sum, difference). • Attribute and cross-network matrices predict a "dependent" network. • Permutation tests, so no assumptions made about the distribution of data.	• Theories formulated tie level (Block et al., 2019). • When working with more than two data points, the STERGMs (implicitly) requires equidistant observations (Block et al., 2018). • Interdependent longitudinal data. • Tie based modelling based on tie formation and tie dissolution. • Tie formation is independent of dissolution within the time step; Markov dependent between time steps.	• Theories formulated at the actor level (Block et al., 2019). • Continuous-time. • Network dynamics by consecutive tie change decisions taken by actors. • Interdependent longitudinal whole network data • Actor-based modelling: the actor "decides" to maintain (endowment), create or dissolve a tie. • A so-called ministep is the time-unit in which a change can occur in a tie or behaviour (i.e. attribute). An actor gets the opportunity to make one change each moment. • The network change is determined by the evaluation function (e.g. mainly determined by the probability of change of the network) and objective function (i.e. probability of behavioural change). • Continuous time modelling (also when the measurements are at discrete time points). First, measurement is not modelled but used as a conditional.
Distributional assumptions	• Permutation test (Monte Carlo).	• Markov dependence assumption, which extends the modelling based on a dyad. Two dyads are assumed to be independent when they do not share a common node (i.e. conditionally dependency).	• The process of change is stochastic. • Simulation based on data (Continuous Markov chain). • Networks need to be stable enough to estimate the model.

(Continued)

Table 1. (Continued).

Approach	MRQAP	STERGM	SAOM
Requirements network data	Dichotomised network data (transformed into matrices).	Dichotomised directed and undirected network data.	- Dichotomised directed network data. - Complete networks of 20–400 actors - At least two measurements with sufficient stability (i.e. measurements not too separate over time). - Test hypotheses related to network co-evolution.
Inferences	Testing whether covariates are associated with certain whole network structures.	- Testing whether certain configurations (such as reciprocity, transitivity) would occur more often than we would expect by chance. Enables inferences about the tie patterns in the network. - Can model multiple time points simultaneously (in the same model). - Modelling of ties relationships (network structures). - Capturing changes of network structures. - Vast literature on exponential family models (of which the ERGM is a member) so properties of the ERGM as a statistical model are well-understood.	- Jaccard index suggests prior to the analysis whether networks are stable and a model fit is attainable. - Modelling changes in social network structures and attributes; - Easy to fit or solutions are available for fitting problems; - Disentangling selection and influence processes; Convergence is relatively convenient to achieve and indicated by t-ratios for convergence and the overall maximum convergence ratio. - Rerunning the model might be a “simple” solution for obtaining convergence. See for further recommendations Ripley et al. (2024)
Disadvantages	- Transforming the covariates into matrices. - Does not capture structural change (formation and dissolution). No underpinning theoretical model. - Including multiple timepoints in models would encounter an issue of multicollinearity. - Tests degrade under simultaneous conditions of extreme skewness and high spuriousness (Dekker et al., 2007).	- Challenging to fit the data with the model. - Interpretation of parameters and consistency of results difficult because of requirement for timepoints to be equidistant. - Only structural information included. - Inability to predict rare events such as the creation of new ties in a sparse network (Block et al., 2018).	- A large number of changes would contradict the assumption that the change process under study is gradual or, in case the change is gradual, would mean that the measurements are too far apart (T. A. B. Snijders et al., 2010). - Inability to predict rare events such as the creation of new ties in a sparse network (Block et al., 2018). - Interpretation of parameters can be challenging. - High response rate (c. 80 %) needed. - Results are in log-odds, which can be “... counter-intuitive and challenging to interpret” (Jaccard, 2001, p. 10) - R package RSIENA (Ripley et al., 2024)
Interpreting results	Conventional interpretation of regression coefficients.	- Results are in log-odds, which can be “... counter-intuitive and challenging to interpret” (Jaccard, 2001, p. 10) - R package <i>statnet</i> (Statnet Development Team, 2019).	
Selected software	- R package <i>asnipe</i> (Farine, 2019). - R package <i>sna</i> (Butts, 2016). - UCINET has features for using MRQAP (Borgatti et al., 2024)		

(Continued)

Table 1. (Continued).

Approach	MRQAP	STERGM	SAOM
Empirical case example (see Illustration in pre-service teacher network data)	• Previous time points are significant positive predictors for communication at the future time point. Program is a significantly negative predictor from M1 to M2, and M2 to M3. Trust only is a significantly positive predictor from time points M3 to M4. Self-efficacy only is a significantly positive predictor from M2 to M3.	• Hierarchy plays a role in tie formation and dissolution in the communication networks of these mathematics trainees, with a weak anti-egalitarianism (less cyclical) dynamic.	• Trainees tend to reciprocate communication ties and form groups. In triads, it is less likely that trainees reciprocate the communication ties when they form a group. Ties fluctuate over alters in relation to attributes like gender, trust and self-efficacy.
Suggested literature	Borgatti et al. (2024).	Lusher et al. (2013), Krivitsky and Handcock (2013)	T. A. B. Snijders (2001, 2005, 2010) Ripley et al. (2024). Brouwer and Froehlich (2023)

(Daly & Chrispeels, 2008; Hoy & Tschannen-Moran, 2003). Respondents answered on a 9-point Likert-type scale (1 = very strongly disagree to 9 = very strongly agree). Internal consistency of the scale was high (α (6 items) = 0.95, calculated over M1, M3, and M4, trust was not measured in M2). The scale *self-efficacy* includes classroom management, student motivation, and instructional skills (Tschannen-Moran & Hoy, 2001) with items, such as ‘How much can you do to get children to follow classroom rules?’, ‘How much can you help your students value learning?’ and ‘How well can you provide an alternative explanation or an example when students are confused?’ Participants answered on a 9-point Likert-type scale (1 = not at all to 9 = always). Internal consistency of the scale was high (α (12 items) = 0.96, calculated over all waves). For both scales, we used the unweighted mean of all items. Finally, the dataset includes dichotomous attributes for gender and program type. The response rate was at least 80% for each time point, which is acceptable (Ripley et al., 2024). As ‘deletion methods are commonly used and the default for most statistical programs’ (Krause et al., 2020, p. 101), we decided to use the default settings for the software used in this study. Given the nature of the social network dataset, we felt it was outside the scope of this article to include other missing data treatments, especially as Huisman and Krause (2018) show this is a complex affair. This is a limitation of our study; further research should explore to what extent other model-based methods and imputation methods influence the outcomes. For more information about the procedures used to collect this data, we refer to previous studies (Bokhove & Downey, 2018; Brouwer et al., 2020).

Descriptive network statistics

Visualisations and descriptive statistics are useful as a first step to gain some insight into the network data. We mainly present these now to provide context for the three data analysis approaches.

Figure 1 and Table 2 represent the evolution of the networks at the four timepoints. Figure 1 suggests that the network at timepoint 1 is ‘denser’ than at the other time points, i.e. nodes are more clustered at the first time point. Density is calculated as the actual number of ties divided by the possible ties, whereas reciprocity is the proportion of actual mutual ties divided by the possible mutual ties (Borgatti et al., 2024).

Table 2 shows that density is decreasing over time in the communication network in mathematics teachers and reciprocity decreases initially and then increases over time. A potential explanation for the decrease in density is that connections often decrease during an academic year, due to pre-service students having placements in schools, and thus fewer contact moments later in the academic year than in the beginning of the academic year. Furthermore, the number of actors decreases over time as well due to drop-out. The changes in reciprocity might be due to the challenging nature of learning how to teach, with a need for more support from other trainees increasing in the later stages of the year, due to what sometimes is referred to as ‘wobble week’.

The more advanced analytical approaches that now follow can be held against this general description of the evolution of the networks.

Analytical approach

In applying the three methods to our data, we employ the following approaches as described before: MRQAP, STERGM, and SAOM.

Data analytical approach for MRQAP (study 1)

For MRQAP, we address the research question whether the attributes gender, program, trust or self-efficacy predict the development of communication networks. As MRQAP does not look at structural changes over time, for this method we included covariates to see if they predicted

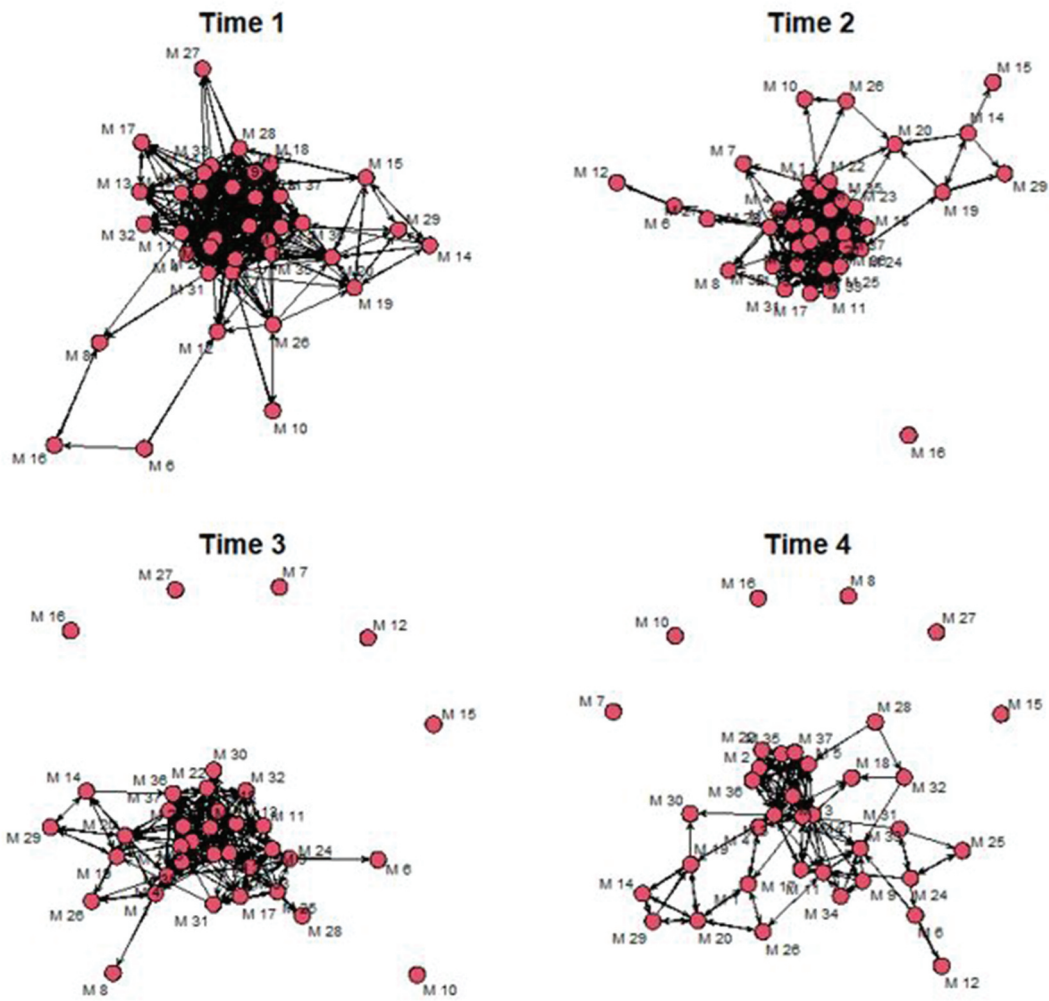


Figure 1. ‘Animation strip’ of the four timepoints M1, M2, M3 and M4. Created with the statnet package.

Table 2. Density and reciprocity of the communication network of maths pre-service teachers for timepoints M1-M4.

Timepoint	Density	Proportion reciprocity
M1	0.315	0.635
M2	0.236	0.622
M3	0.193	0.685
M4	0.115	0.742

future network compositions. As MRQAP is a permutation test, it makes no assumptions about the distribution of data. MRQAP models were fitted to all four mathematics networks M1, M2, M3 and M4 with four predictors. We built three series of models, with the communication network at the first time point M1 as predictor of that at the second time point M2, M2 for M3 and M3 for M4. The main analyses were conducted with functions in the *asnipe* (Farine, 2019) R package (`mrqap.dsp` command, DSP estimation with 10 randomisations). Initial models were built including the communication network from the previous time point, and then each

covariate (gender, program, trust and self-efficacy) by creating similarity, sum, and difference matrices as appropriate for each covariate. *Gender* and *program type* matrices were based on similarity, i.e. a score of '1' in the matrices meant that two trainees have the same gender or program. The matrix for *self-efficacy* was based on a difference between self-efficacy of trainees, under the assumption that a large difference might influence 'help-seeking' from one trainee to another. The matrix for *trust* was based on the sum score of trust, under the assumption that the total amount of trust for a pair of trainees might influence communication between trainees. MRQAP is conservative with respect to missing data, and if one predictor or outcome or variable is missing, data in the corresponding position of all other variables matrices is treated as missing. In our data, this meant that at most 9 out of 37 data points were excluded, indicated by 'NA' in the accompanying R code.

Data analytical approach for STERGMs (study 2)

For STERGMs, we specify the same terms in both the formation and dissolution model (Statnet Development Team, 2019). We address the research question how likely it is that reciprocal relationships are formed. We utilise the R package *statnet* for these analyses (Butts, 2016). With the R package *tergm* from the *statnet* package each network was converted to a network object, and these were collected in one list. Models were then fitted with the *stergm* command. The models were fitted using three parameters: a formation formula which described the mechanism for forming ties, a dissolution formula which described the mechanism for dissolving ties, and an estimation method (Monte Carlo maximum likelihood estimation). These tie-based models were fitted for different sets of time points. In most practical situations not all these possibilities would have been looked at, but as the focus here is methodological, rather than substantive, we included all four time points M1 to M4, three time points for M1 to M3, and M2 to M4, and the subsequent pairs M1:M2, M2:M3 and M3:M4. In STERGMs the term 'mutual' refers to 'reciprocity'.

Data analytical approach for SAOMs (study 3)

We model SAOMs in the package Simulation Investigation for Empirical Network Analysis (SIENA, Ripley et al., 2024), which enables us to model the change of the communication networks while controlling for cross-network effects (support for developing strategies, friendships) and individual attributes like gender, self-efficacy and trust. For the participating mathematics trainees, we looked at selection in communication peer-networks, i.e. initiating connections with others and specifying one model across the consecutive waves (i.e. from M1 to M2, from M2 to M3, and from M3 to M4). Prior to modelling, we checked the Jaccard Similarity index which indicates whether the stability in the networks is sufficient to estimate the model (Snijders, 2001; Snijders et al., 2010). This actor-based model includes network effects by default. A basic rate parameter denotes the change rate in communication over time. Outdegree/density is the tendency of trainee teachers to make (or break) communication ties to their peers regardless of any other processes, with reciprocity referring to the formation (or breaking down) of mutual ties. In addition to these basic network effects, the models include the tendency of group formation, so-called transitive triplets and transitive reciprocated triplets (i.e. transitivity), which can be recognised as 'triangles' in a network. The models also include cross-network effects of the previous time point, e.g. the impact of friendship networks. Finally, the models include demographic covariates of the development of the communication peer-networks: self-perceived self-efficacy, trust, gender (female compared to male), and program type, i.e. ego, alter, and similarity effects. For example, a positive ego self-efficacy effect means that the higher the self-efficacy, the more likely it is that someone is active in forming connections (more outgoing ties); a positive alter self-efficacy effect means that the higher a score on self-efficacy, the more likely it is that someone is popular in the network (more incoming ties; a positive similarity effect means that two actors who are more or less similar in

their self-efficacy score, the more likely that they form a tie. We use the data-analysis package RSIENA (Ripley et al., 2024) within the statistical software (RCore Team, 2021; R Studio Team, 2021). For estimation, the Robbins-Monro algorithm is used in the models according to the Method of Moments (Ripley et al., 2024, p. 79). RSIENA allows missing data on network variables, on covariates, and on dependent variables.

In sum, we can contrast the three methods as follows:

- (1) MRQAP models included covariates but no structural effects. For MRQAP, the research question is whether attributes predict the development of communication networks, where the model is correlational between variables.
- (2) STERGMs were estimated without covariates but with structural effects. For STERGMs, the research question is about the likelihood of forming reciprocal relationships, where the model is tie-based.
- (3) SAOMs were estimated with both covariates and structural effects. For SAOMs, the research question is about the change of the communication networks while controlling for structural effects, cross-network effects and individual attributes. More specifically, they yield information about selection and/or influence mechanisms in networks, where the model is actor-based.

Findings empirical example

In this section, we report on the results of the illustration of the three methods, respectively: MRQAP, STERGMs, and SAOMs, in network data of pre-service teachers. As the focus is more on comparison of the three methods, we have chosen to not present all the results tables in this text, but present a narrative summary of the findings. The Supplementary materials show the detailed results of the different social network analyses of maths teachers (see Tables S1 to S4). Based on the MRQAP-analysis (Study 1; Table S1), we could conclude the following. First, in all final models, the previous time points are significant positive predictors for communication at the future time point. Second, in all final models, *Program* is a significant negative predictor. Third, *Trust* is only a significant positive predictor from time points M3 to M4.³ Fourth, model fit, as measured by adjusted R-squared (percentage of variance explained by the model), over the time points ranged from 0.27 to 0.45.

For the STERGM (Study 2; Table S2), we see that when including all time points (M1 to M4), a relationship is much more likely to form if it will close a mutual pair; the conditional log-odds are increased by 2.16 which translates to an increase in the conditional odds of $e^{2.16} \approx 8.67$. The reciprocity/mutual effect on dissolution also is positive and significant; the point estimate is an increase of 1.98 in the conditional log-odds of dissolution which implies that reciprocal/mutual ties are likely to dissolve. The coefficients for transitive ties (hierarchical triads) are positive and significant for both formation and dissolution. The coefficients for cyclical ties (egalitarian triads) are negative for both models, with only some of the model for dissolution significant at the .05 level. Overall, these results suggest that hierarchy plays a role in tie formation and dissolution in the communication networks of these mathematics trainees, and there might be a weak anti-egalitarianism dynamic. We can observe that model fit is better with fewer time points included, as those models exhibit lower AIC and BIC values. Technically, the interpretation of coefficients in terms of log-odds can make interpretation ‘... counterintuitive and challenging to interpret’ (Jaccard, 2001, p. 10). Intuitively, the modelling process of a STERGM can be compared with an omnibus test like an ANOVA: has *any* tie formation taken place across the included time points? Overall, we see a significant positive log-odds for transitivity in formation over time points M1 to M4 (0.91). However, zooming in on specific time periods it seems that from time point M1 to M2 and M3 to M4, the log-odds are non-significant (0.66 and -0.06 respectively). This should be kept in mind while interpreting results over multiple time points.

As the SAOM approach focuses on underlying change processes, four measures of change are included (Study 3; Tables S3 and S4). We can address the research question of whether maths teachers select their peers in the communication network based on support for their teaching strategies. When starting modelling in RSIENA, we checked the stability for the communication networks by looking at the Jaccard index. The Jaccard index was between 48% and 50%, which is above the heuristic value of 30%. We could expect sufficiently gradual change over time to estimate the model in RSIENA (see Ripley et al., 2024). Subsequent models of change, for pairs of consecutive waves, show that networks have significantly positive reciprocity coefficients and positive transitive triplets parameters, except from M3 to M4. This means that trainees tend to reciprocate communication ties and form triadic groups. In triads, it is less likely that trainees reciprocate the communication ties when they form a group (negative transitive reciprocated triplet parameter from M1 to M2 and M2 to M3).

Considering the research questions in detail, we see that the three methods answer different questions. With MRQAPs we aimed to find out whether attributes predict the development of communication networks. We saw that previous time points are significant positive predictors for communication at the future time point, with *Program* a significantly negative predictor, and *Trust* only a significantly positive predictor from timepoints M3 to M4. The STERGMs focussed on how likely it is that reciprocal relationships are formed. Our analysis showed that hierarchy plays a role in tie formation and dissolution in the communication networks of these mathematics trainees, with a weak anti-egalitarianism (less cyclical) dynamic. Finally, our SAOM focussed on change of the communication networks while controlling for cross-network effects and individual attributes. We could conclude that trainees tended to reciprocate communication ties and form groups (positive estimate for reciprocity). In triads, it was less likely that trainees reciprocated the communication ties when they formed a triadic group (negative effect for transitive reciprocated triplets). However, the main interest in SAOMs are the dyadic cross-network effects and the attribute-related effects (in this selection model). When individuals are friends, it is more likely that they communicate (positive estimate for friendship peer network). When maths trainees search for more support for their teaching strategies, it is more likely that they communicate with their peers at the beginning and at the end of the academic year (positive effect for teaching strategies peer network). We identified a homophily effect for attending the same school programme (positive estimate for school programme).

Given our analyses, we did not observe overt contradictions between the findings of the social network structures. These methods can be used in complementary ways but the different techniques provide insights in other aspects, e.g. STERGMs in social network structures and SAOMs in social network mechanisms based on actor attributes, which go beyond the correlational character of MRQAPs. MRQAP provides a fairly straightforward and relatively easy to interpret method for looking at the development of networks. However, MRQAP does not capture structural changes in social networks and lacks a theoretical model for the formation and dissolution of ties. Instead, MRQAP focuses on how the network as a whole develops based on specific factors included in the model. In contrast to conventional OLS regression methods, MRQAP models account for the interdependence of networks. Depending on whether analysts want to emphasise tie formation or actor decisions, STERGMs or SAOMs can both provide a more fine-grained lens for examining the (co-)evolution of networks. STERGMs and SAOMs are considerably more complex models, but they open analytical doors that other methods often can't reach.

This brings us to the requirements that enable the researcher to select the most appropriate longitudinal social network analysis method by considering the aims, research questions, assumptions, and advantages and disadvantages. Table 1 shows that several aspects can guide the researcher in selecting the analytical approach a priori. We summarise the key considerations with the acronym 'FACTS', i.e. Focus, Assumptions, Conceptualisation, Time points, and Size. These aspects are important for selecting the appropriate analysis approach (see for a flow chart Figure S2). Firstly, an analyst should consider the *Focus*: Is the analyst interested in analysing whole networks in light of

covariates (MRQAP), the ties in those networks (STERGMs) or actors (SAOMs). This focus is determined by the study aim and research question(s). With Focus the research context should also be considered, for example, curriculum phases which might impact relationship development. Secondly, each method has its own *Assumptions*, with MRQAP not assuming any distribution through permutation tests, STERGMs assuming dyads are independent and not sharing a common node and SAOMs assuming stability of the networks over time. Thirdly, all methods require theoretical *Conceptualisation* which informs the model building. Fourthly, the nature of the *Timepoints* over which network data was collected plays a role. With regular and consistent network measurements, MRQAP and STERGMs can be used, but if the time between measurements of complete network data isn't equidistant then SAOMs are more appropriate. Finally, an analyst should consider the *Size* of the networks, as both STERGMs and SAOMs are less suitable for large, sparse networks (400+ nodes). We contend that considering FACTS is relevant for longitudinal network analyses in general. To illustrate the acronym FACTS, let's consider interactions between teachers and students in a mathematics education classroom from a social network perspective (see Bokhove, 2018). The first question to ask is whether the *Focus*, depending on the aim, research questions and context, is on the classroom as a whole, the interactions among dyads (i.e. two students), or the behaviour of students as actors. This already might necessitate a particular data analysis approach suitable for analysing the whole classroom, the nature of the interactions, or actors. This also involves *Assumptions*: perhaps the focus on teacher *and* student interactions contradicts the assumptions of STERGMs and SAOMs regarding the network boundary and interdependency, and so the analyst will have to ascertain whether these approaches can still be used. This then leads to a particular *Conceptualisation* of the classroom context one wants to model; for example, we might decide to focus on students' interactions and behaviour over time. Decisions also depend on whether there are irregular or fixed observations intervals, i.e. *Time points* within and between lessons. In this case, we could observe classroom interactions not far apart during a lesson. However, if classroom interactions are too rapid, this might pose a challenge. Finally, a classroom context is bound to be limited in *Size* of the network, so this also has to be considered. In a classroom, we might have around 30–40 actors. Given these FACTS, a priori this might point towards SAOMs as being an appropriate analysis method for this context (Bokhove, 2018, p. 23). Whichever analytical choice is subsequently made for a context based on FACTS, the findings can only be considered in light of that context as well, with an analysis perhaps yielding different recommendations for different contexts. As our focus here was on a *methodological* contribution, we do not elaborate further on this, but refer to our previous work (Bokhove & Downey, 2018; Brouwer et al., 2020).

Conclusion and discussion

Social networks methods have become very popular in the educational and psychological sciences (e.g. Broda et al., 2023; Brouwer & Froehlich, 2023; Gilman et al., 2022; Sweet, 2016). As networks arise in many situations where individuals interact, it is useful to study social network structures, patterns of interactions, and how networks evolve and change over time. This article provides an overview of three commonly applied longitudinal or dynamic SNA approaches, i.e. MRQAP, STERGMs and SAOMs. In line with Block et al. (2019), we argue that understanding the research context, requirements of the data and the underlying social processes is required. Importantly, model selection should be based on theoretical considerations. Furthermore, we should take into account the limitations of the models, such as not capturing social network structures (MRQAP), challenges with convergence of the models, especially in large networks (STERGMs), or the challenge of interpretation of the effect parameters and sufficient response rate (SAOMs). These issues are easily overlooked when we focus too much on advanced statistical techniques; they are, after all, a means to achieve a better theoretical and practical understanding of social phenomena.

Future research can inform the reader about other advanced and newly developed longitudinal social network models, for example, Autologistic Actor Attribute Models (ALAAM; Parker et al.,

2022) or the Group Partitioning Model (Hoffman et al., 2023). The former can be used for investigation of contagion based on attributes, whereas the latter can be used for investigation of the portioning of clusters or communities within the social networks. Both models can be complex in terms of data requirements, computations, or interpretation of the effects. Although both models are originally cross-sectional, more insights might be obtained when applied in longitudinal social network data (de Matos Fernandes et al., 2024; Hoffman et al., 2023; Parker et al., 2022; Snijders et al., 2006). Another recommendation for further research is to apply and compare (longitudinal) social network models in other psychological and educational contexts, such as primary, secondary education or organisations. It might also be informative to consider research fields other than psychology and education, such as environmental sciences to see, for example, how networks impact climate change behaviour (cf., Severijns et al., 2023) or policy making or legislation (Battaglini & Eleonora Patacchini, 2019). Regardless of the discipline where longitudinal networks are applied, consistent with FACTS, researchers should *focus* on the aims, research questions and context, consider the model *assumptions*, *conceptualise* the theoretical concepts and links that inform the model building, consider *time points* between the measurements, and consider the required network *size*. With the focus, the researcher should also take into account the research context rather than merely interpreting model effects and consider theoretical and practical implications, such as network support interventions for preservice teachers (Alwafi et al., 2020). Furthermore, a deeper exploration of the factors driving changes in network structure – such as seasonal variations, curriculum phases, and peer dynamics – can offer valuable insights into the observed patterns. Overall, comparing three widely used models for analysing longitudinal social network data will enable readers to make well-informed, evidence-based decisions in their own research.

Notes

1. In Web of Science <https://www.webofscience.com/> the combination of ‘networks’ and ‘MRQAP’ yields 16 publications and more than 600 citations in the last five years.
2. Note that we have quoted ‘larger than 2 in absolute value’ from Ripley et al. (2024, p. 82). The threshold at the 5% level is actually slightly less at 1.96.
3. Note that we could not add trust from time points M2 to M3 because trust was not measured at timepoint M2.

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