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Modeling the Joint Dynamics of Relational Events and Individual States

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***Abstract*—Networks evolve at multiple levels; edges or relations may change, and the characteristics of the individuals within the network may change as well. Often these processes are intertwined, and in order to study them, statistical models must be developed that account for coevolution of multiple network components. The increased availability of continuous time network data has prompted new models for network inference such as the relational event framework. While network data may be continuously observable, the characteristics or state of an individual can still only be observed periodically. This type of panel data can be readily analyzed using actor-oriented models, but these methods do not accommodate continuous network data. We propose a model that integrates the relational event framework with actor-oriented models for behavioral change, allowing us to model the joint dynamics of relational events and individual states. This composite model preserves the advantages of each method, while leveraging the richer information available in relational event data. We apply our model to datasets collected from virtual team experiments to highlight the utility of our method.**

Keywords—relational events; actor-oriented models; coevolution; longitudinal networks; teams

I. Introduction

Increasingly, social network data can be collected in the form of time-stamped actions taken by individuals within a network. The abundance of these electronic sources such as email, social network sites, and other digital traces provides new means of studying social interaction [1]. Methodologies such as proximity monitors allow researchers to identify interaction patterns that are similar to but distinct from self-reported friendship ties [2, 3]. These examples help mark the rise of social network analysis as a modern science encompassing dynamic, temporal data [4]. Under this new data paradigm, traditional approaches quickly become outdated and a new perspective on networks is needed [5].

Because of the inherently dynamic nature of this class of data, new quantitative models for social network analysis are required. Relational event models (REM) are statistical tools designed to predict how generative behavioral, cognitive, and social mechanisms contribute to future actions in a network [6]. The primary advantage of the relational event framework is that the exact sequence and timing of actions may be directly observed. Due to this high temporal granularity, distinct patterns can be modeled, including exogenous effects, endogenous effects, node or relational covariates, and environmental effects [7]. While REM is an effective tool for predicting behavior, network ties are only one level of analysis. In a longitudinal network, multiple dynamic processes may be occurring simultaneously and at multiple levels. Specifically, attributes of the nodes themselves may evolve over time as a result of prior relational events, and the changing states of these attributes may influence future relational events. For example, [8] studied the evolution of smoking – a node attribute – co-occurring with friendship links. This type of process is a coevolution, the joint dynamics of two or more processes over time. In Fig. 1 we illustrate joint node and edge dynamics.

The notion of coevolution has been incorporated in traditional stochastic actor-oriented models (SAOM) [9]. Typically, longitudinal data is collected at discrete time points, in which individuals are surveyed. Their responses provide network data as well as information on opinions, feelings, or attitudes. The key drawback to this method is the lack of granularity; the micro-level changes that inherently must occur over time are impossible to know, and as a result simulation must be used to “guess” why the results are what they are. Under the relational event paradigm it is possible to know half of this social equation. In particular, the exact sequence of events that occurred from point A to point B is now visible, and can be used to inform our inference on the behavioral changes. However, information about an individual, particularly their thoughts or feelings, are not readily observable.

Our contribution is an extension to the relational event model that incorporates the joint dynamics of node-level behaviors and attributes. Because changes at the individual level often cannot be observed continuously we maintain the structure and logic of stochastic actor-oriented models, but incorporate relational event data. The observed relational event sequence may replace the simulated network micro-steps that constitute the model’s estimation, leading to a higher degree of fidelity and greater freedom in defining sufficient statistics. To illustrate the utility of this integrated framework, we analyze experimental data collected from individuals playing a simulated strategy game in a team environment. Our dataset

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Fig. 1. A graph observed at two periods in time, moving from left to right. The colors of the nodes represents their behavioral state (in this case, one of two categories). The edges are links between the nodes. A coevolution model captures any process in which nodes and edges may change together over time.

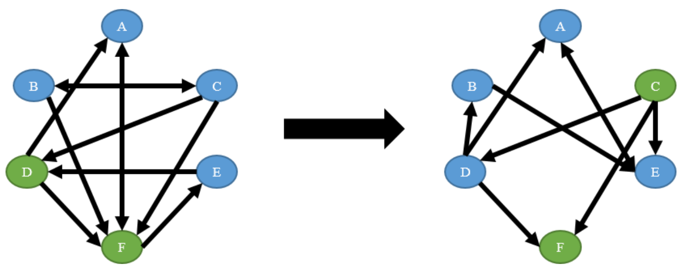
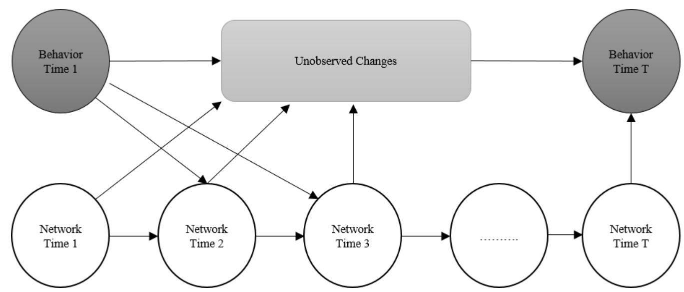


Fig. 2. The temporal dependence structure between individual behaviors and networks. The observable information is the behaviors at survey times and a continuous view of the network. The intermediate changes in behaviors cannot be observed, but must be modeled. Arrows indicate direction of influence.



includes a continuous transcript of communication recovered from chat logs as well as multiple waves of survey responses. We discuss our initial findings and implications for future research.

II. Integrating Event Networks and Individual State Changes

The coevolution of network events and individual state variables encompasses the joint dynamics of both interactions and the thoughts, states, or behaviors of the individuals within the network. This process unfolds in continuous time; at any given point, there is a network in which people are embedded, and each of these people resides in a particular state (e.g. they are a smoker, or they have a positive opinion of their boss, etc.). Prior work considered the case of the network and individual states being captured as snapshots at discrete points in time, e.g. [9]. This type of panel data is generally collected through surveys or a single scrape of information. However, digital trace data such as email, call logs, and proximity monitors make the communication process more transparent. These timestamped messages constitute a continuous observation of network dynamics.

Unfortunately, collecting continuous data for individual states is more difficult. Some characteristics are observable, such physical attributes or behaviors. When studying virtual data – e.g. video games or blog posts – data about the individual user can be determined. In general, human characteristics are much more difficult to quantify. For example, we may not know a person's political affiliation at any given time. As a consequence, we must continue to collect survey information when studying the dynamics of these latent individual attributes. Despite our inability to observe the continuous evolution of states, it is realistic to assume that they coevolve with the dynamics of the surrounding network. In other words, the behavioral patterns of an individual over time both influence and are influenced by the state of that person. Fig. 2 is a representation of this temporal dependence framework.

We consider first a basic joint probability model, in which the likelihood of the event sequence and the discrete state observations is given by:

$$P(X, Y(t_T) \mid Y(t_0); \Theta) = P(X \mid Y(t_0); \Theta) P(Y(t_T) \mid X, Y(t_0); \Theta) \tag{1}$$

Here, X represents a sequence of network communication events where an event is defined as $x = (i, j, t)$. This unit of information, known as a relational event [6], contains sender, receiver, and timestamp data for each interaction. These events may be expanded to include the weight, valence, modality, or type of message [10-12]. The variable Y represents the realization of the individual states we are modeling; it is possible that there are multiple types of states and multiple time points, but for simplicity we consider the case of one type observed at two points. The set Θ is a collection of parameters defining the probability function, which we will specify.

In (1), we expanded the likelihood using basic conditional probability rules. From this modification, we observe two natural components of the likelihood: first, the probability of the observed event sequence, given the known initial state values; second, the probability of ending up in the final state, $Y(t_T)$, given the initial state $Y(t_0)$ and the event sequence X that transcribed between the two observations. Assuming that these probability densities are governed by separate parameters, we can consider the likelihoods separately.

A. *Modeling Continuous Network Dynamics*

The first component – the conditional likelihood of the event sequence – is equivalent to the general formulation of the relational event framework [6]. In a relational event model, techniques from event history and survival analysis are used to determine the relative rates of each type of interaction event. The occurrence of events is equivalent to arrivals from a Poisson process with a piece-wise constant rate [13]. The probability of a specific temporal sequence is computed by taking the product of each event's hazard rate (instantaneous propensity of that event occurring) multiplied by the survival function for all possible events (the likelihood that no other event occurred first). The mathematical form is given as:

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$$P(X \mid Y(t_0); \boldsymbol{\theta}) = \prod_{e=0,\dots,M} \lambda_{i_e j_e}(t_e; \boldsymbol{\theta}) \times \exp\left(-\Delta t_e \sum_{(a,b)\in A_{t_e}} \lambda_{ab}(t_e; \boldsymbol{\theta})\right) \times \exp\left(-(t_T - t_M) \sum_{(a,b)\in A_{t_T}} \lambda_{ab}(t_T; \boldsymbol{\theta})\right). \tag{2}$$

The final term in (2) represents the likelihood of no arrivals in the time between the final event observation t_M and the censoring time t_T. The functional form of the hazard rate is given by $\lambda_{ij}(t) = \exp(\theta' \boldsymbol{s}(i,j,t))$ where $\boldsymbol{s}$ is a vector of sufficient statistics computed from the event history up to time t, as well as any attribute or state information.

Because we have access to complete information, we may directly infer the model parameters from this likelihood function. For a given set of specified sufficient statistics, we may either use maximum likelihood estimation or Bayesian inference to recover the optimal θ. These parameters are independent of the behavioral dynamics, and can thus be fit independently.

B. Modeling Continuous Behavior Dynamics

The second component of the likelihood function is the state transition probability. This value is modeled following the logic of [9]. In this prior framework, a social network was simultaneously observed with a set of states, representing behaviors such as smoking or drinking [8]. The basic assumption of these models is that the observed changes are an outcome of an underlying stochastic process, whose transitions are the result of small changes. This logic that the Markov process advances according to an unobserved series of individual events is a consistent component of stochastic actor-oriented modeling, and follows from the work of [14]. These actions are known as micro steps [8], and occur continuously during the observation period. To determine the mechanisms that produced the observed changes, we need to explicitly model the architecture of a micro step. There are two components to this process that need to be detailed: the rate of change for each network actor, and the objective function that governs that nature of the change.

The assumption of an underlying Markov process directly implies that occurrences of an actor making a change are arrivals from a Poisson process, with a rate that is potentially unique to that agent. In prior work and in our model here, the rate for each actor is given as an Exponential function of rate parameters and sufficient statistics [15-17]. To model the direction of change, we employ the fundamental assumption of a stochastic actor-oriented model that individual agents change their network in such a way that the new network topology is more satisfactory, given some internal objective function. Extending this definition to include behavioral states, we model the decision of which change to make as the result of an objective or utility function. A convenient form of this function is a linear combination of utility parameters and sufficient statistics, computed from the state of the stochastic process. If we assume that the errors in the utility functions follow an extreme value distribution, then we may express the probability of change as a multinomial logit model [18].

Similarly to our continuous network model, we would like to model the behavioral state transitions as a sequence of events whose likelihood is given by the components outlined previously. However, we do not have access to this continuous sequence. Following the logic of [19], we *augment* our observed state data by simulating sequences of possible micro-steps. In order to make use of the exact temporal data afforded by the relational event network, we alter the augmentation procedure slightly to produce timestamps for the simulated events. The event simulation procedure is defined in Table 1. The values used in Table 1 are

$$\pi_{i_r}(y(t_r), x(t_r); \rho, \boldsymbol{\alpha}) = \rho \exp\left(\boldsymbol{\alpha}' \boldsymbol{s}\left(i_r, t_r, x(t_r), y(t_r)\right)\right)$$

with the choice likelihood:

$$p_i(\, y(i_r \updownarrow \delta) \mid y(t_r), x(t_r); \boldsymbol{\beta}\,) = \frac{\exp\left(\boldsymbol{\beta}' \boldsymbol{s}\left(i_r, t_r, x(t_r), y(i_r \updownarrow \delta)\right)\right)}{\sum_{\tau\in\{-1,0,1\}} \exp\left(\boldsymbol{\beta}' \boldsymbol{s}\left(i_r, t_r, x(t_r), y(i_r \updownarrow \tau)\right)\right)}.$$

Here, ρ and α are parameters governing the rate of change, and β are parameters governing individual decisions. The value δ is the amount of positive or negative change in the attribute. Finally, we model the time between the change events as an Exponential random variable with mean equal to the sum of the individual rates

$$\lambda_+(t_r) = \sum_i \pi_i(y(t_r), x(t_r); \rho, \boldsymbol{\alpha}).$$

Now, the probability of the augmented sequence V, given all of the observed components is the following expression:

$$P(V \mid X, Y; \rho, \boldsymbol{\alpha}, \boldsymbol{\beta}) = \prod_{r=1}^{R} \pi_{i_r}(y(t_r), x(t_r); \rho, \boldsymbol{\alpha}) p_i(\, y(i_r \updownarrow \delta) \mid y(t_r), x(t_r); \boldsymbol{\beta}\,) \times \prod_{r=1}^{R} \exp\{-(t_r - t_{r-1})\lambda_+(t_r)\} \times \exp\{-(t_m - t_R)\lambda_+(t_R)\}. \tag{3}$$

Snijders, Koskinen and Schweinberger [19] showed that by taking the score function of (3) and using an iterative stochastic approximation method [20], we will find a solution to the parameters ρ, α, β. These parameters can then be plugged into the procedure in Table 1, yielding a new sequence V. The process is repeated until the parameters converge. For sake of brevity we omit full details here.

C. Specifying the Model

In order to fully specify the rate functions and decision functions, we need to determine a set of sufficient statistics which influence the model component values. The primary divergence of event network modeling from traditional actor-oriented approaches is due to the reliance on the accumulation of relational events over time. SAOM's rely instead on multiple discrete observations of fixed graph structures. Therefore, the network statistics derived in past work is purely structural [9, 16, 17]. These signatures are analogous to those calculated in single-stage exponential random graph models (ERGM) [21]. However, event data can be used to create more complex signatures that capture the volume and pattern of interaction better than dichotomous structures; for examples, see [6, 10, 22, 23]. For sake of notation, we denote $\omega_t(i,j)$ to be the number of relational events sent from i to j up to time t, potentially weighted by time [10]. We present a number of sufficient statistics for predicting both behavioral change and network evolution.

1) Statistics for Behavior Change

There are three primary types of statistics for predicting behavior change: endogenous effects, exogenous network effects, exogenous behavioral effects, and fixed effects. An endogenous variable is a function only of the history of behavioral states. For example, a common metric is positivity, which captures the tendency for those with large values to make more or less frequent change.

$$s_{positivity}(i,t) = y_i(t)$$

Another potential endogenous statistic is attribute-based assimilation. This metric captures the tendency for an individual's state to become more similar to those that share some fixed attribute. In other words, people that are homogeneous in some dimension become more similar.

$$s_{a-assimilation}(i,t) = \sum_{j\neq i} \mathbf{1}\{a(i)=a(j)\} \times \left(1 - \frac{|y_i(t) - y_j(t)|}{R}\right)$$

In the above statistic, $1\{a(i) = a(j)\}$ is an indicator function that is equal to one if the attribute of i, $a(i)$, is equal to the attribute of j. R is the range of values for behavior y.

Exogenous statistics for predicting behavior change are those that include the relational event history. Simple examples include in and out-degree, which measure the frequency with which an individual receives or sends relational events, respectively. A positive effect of in-degree implies that an agent is more likely to change behavior if they receive a high volume of communication.

$$s_{indegree}(i,t) = \sum_{j\neq i} \omega_t(j,i)$$

$$s_{outdegree}(i,t) = \sum_{j\neq i} \omega_t(i,j)$$

TABLE I. SIMULATION PROCEDURE TO GENERATE AUGMENTED SEQUENCES.

Initialize with $y(t_0)$ and a set of parameters ρ, α, β	
1.	Start with V empty, $r = 0$ and $t_r = t\_0$
2.	Select an actor i with probability $\pi_i\big(y(t_r), x(t_r)\big)/\lambda_+(t_r)$
3.	For that actor, change their state value to $y_i(t_r) + \delta$ with probability $p_i\big(\,y(i \updownarrow \delta) \mid y(t_r), x(t_r)\,\big)$
4.	Augment V with $V = \{V, (i, \delta, t_r)\}$
5.	Set $r = r + 1$. Update the time to $t_r = t_{r+1} + \Delta t$, where Δt is drawn from an Exponential distribution with mean $\lambda_+(t_r)$
6.	If $t_r < t_m$, return to step 2. Otherwise, stop and return V

We may also use relational event accumulation create a communication assimilation effect, where an individual adjusts their behavior to become more similar to those whom they most frequently communicate with.

$$s_{c-assimilation}(i,t) = \sum_{j\neq i} \frac{\big(\omega_t(i,j) + \omega_t(j,i)\big)}{\sum_k\big(\omega_t(i,k) + \omega_t(k,i)\big)} \times \left(1 - \frac{|y_i(t) - y_j(t)|}{R}\right)$$

This statistic essentially takes the weighted average of the discrepancy in attribute values, based on communication frequencies.

An exogenous behavioral effect captures the tendency for a behavior to change in conjunction with changes to a different behavior. This type of measure is useful when considering multiple dynamic behaviors simultaneously. Finally, fixed effects are covariates based on static attributes of the individuals. For example, a fixed effect could be an actor's position in their organizational hierarchy. Such a statistic would imply that behavioral change is influenced by that characteristic of the agent.

2) Statistics for Network Change

Statistics for predicting network change are classified similarly to those for behavioral change, and include endogenous, exogenous, and fixed effects. Because our model assumes access to relational event data, we may employ many of the structural signatures used in prior work on REM's [6, 7, 10]. We consider individual effects such as activity and preferential attachment:

$$s_{activity}(i,j,t) = \sum_{j\neq i} \omega_t(i,j)$$

$$s_{PA}(i,j,t) = \sum_{k\neq j} \frac{\big(\omega_t(j,k) + \omega_t(k,j)\big)}{\sum_l\big(\omega_t(l,k) + \omega_t(k,l)\big)}.$$

We also consider dyadic effects such as persistence and reciprocity:

$$s_{persistence}(i,j,t) = \frac{\omega_t(i,j)}{\sum_{k\neq i} \omega_t(i,k)}$$

$$s_{reciprocity}(i,j,t) = \frac{\omega_t(j,i)}{\sum_{k \neq i} \omega_t(k,i)}.$$

Finally, we utilize triadic effects such as two-paths and shared partners:

$$s_{OTP}(i,j,t) = \sum_{k \neq i \neq j} \sqrt{\omega_t(i,k)\omega_t(k,j)}$$

$$s_{ITP}(i,j,t) = \sum_{k \neq i \neq j} \sqrt{\omega_t(j,k)\omega_t(k,i)}$$

$$s_{OSP}(i,j,t) = \sum_{k \neq i \neq j} \sqrt{\omega_t(i,k)\omega_t(j,k)}$$

$$s_{ISP}(i,j,t) = \sum_{k \neq i \neq j} \sqrt{\omega_t(k,i)\omega_t(k,j)}.$$

In conjunction with these structural signatures, we may also include fixed effects analogously to our measure for behavior change. Finally, we may include exogenous behavioral effects, which incorporate the value of attributes into the statistics. One potential statistic is a similarity effect, in which the propensity for communication is influenced by how similar two actors are in the value of the dynamic behavior.

$$s_{similarity}(i,j,t) = \left|\frac{y_i(t) - y_j(t)}{R}\right|$$

We should note that this list is by no means exhaustive. Any combination of network and behavioral data, plus fixed covariates, can be incorporated into sufficient statistics. The primary requirements are that statistics are finite, linearly independent, and of theoretical interest [6].

D. Model Selection

An important component of statistical inference is the selection of the model which is the best fit to the data. We identify a number of potential criterion for determining which combination of sufficient statistics is appropriate. The most commonly used approach is forward model selection using a likelihood or deviance based measure. This general approach involves testing models with an increasing number of terms and comparing the log-likelihood of each step. Tests such as the likelihood ratio test, a Chi-square test for deviance reduction, or measures such as the AIC or BIC would be appropriate. An alternative approach is to minimize a loss function, which in statistical inference is typically a misclassification rate. In this case, the best model is one that most accurately predicts a subset of data after being trained on a test set. We leave it to the researcher's discretion to determine which method is most appropriate for their application.

III. Application to Multiteam System Identity and Interdependence

To illustrate the types of questions this model may answer, we apply our method to data derived from experiments on cooperative multiteam systems. A multiteam system (MTS) is a group of two or more independent teams that are working towards both local and system-level goals [24]. These organizational units are common in many fields, such as the military, hospitals, and corporations. MTS's face a number of unique challenges due to their organizational structure. Individuals must manage the complexities of cross-team communication in order to be effective at their own tasks [25]. Further, there may be some activities that sacrifice team productivity in favor of system-level goal advancement, and vice versa; these sources of tension between levels are known as countervailing forces [26].

Because the interests of the individual teams may be different from the system's goals, actors within the organization have a constantly evolving sense of identity; in other words, a person may feel fiercely loyal to their small team, or may feel a strong sense of attachment to the system as a whole. Further, we expect individuals to have varying feelings of interdependence, i.e. how heavily they rely on the system, rather than their team for information.

Prior work has applied relational event models to study team and multiteam system communication processes [25, 27, 28]. However, these studies do not consider the coevolution of team process with the thoughts and opinions of the team members themselves. Therefore our exploration of the joint dynamics of communication, identity, and interdependence is a novel approach to understanding teams and MTS.

A. Data

Participants include 300 individuals arranged into fifteen twenty-person multi-team systems. Participants reported to a laboratory in groups of twenty, forming a single MTS, and each MTS experiment was conducted in a separate five hour session. The experimental setting was a computer-based military strategy game with an MTS goal and team-level goals. Participants were randomly assigned to one of four teams within the MTS, and to a specific role within their component team. Each participant was seated at an individual workstation, and performed the task using a laptop computer.

The session consisted of training, a pre-game survey, a short twenty minute practice mission, a second survey, a forty minute full mission, and a final third survey. Individuals in the experiment could communicate via Skype with any other participant; the transcripts of these messages were recovered and converted to relational event data. At each survey point, participants are asked to rate their connection to the MTS on a scale of 1 (very far) to 6 (very close). They were also asked to rate their dependence on other squads for information. A sample question was "My squad needs information and advice from other squads to perform our task well" with responses on a 1 (strongly disagree) to 7 (strongly agree) scale.

B. Operationalization

The communication logs in conjunction with the series of survey responses constitute realizations of the hypothesized coevolution process. From these we may define our independent and dependent variables. The relational event sequence was used to compute the values of ω_t for all pairs at all time points. The survey responses constituted our values for MTS identity $Y_1(t_0)$, $Y_1(t_1)$, and $Y_1(t_2)$, and informational interdependence $Y_2(t_0)$, $Y_2(t_1)$, and $Y_2(t_2)$. We also controlled for the survey responses to questions regarding squad identity and squad interdependence. These added variables allow us to separate opinions regarding the system from opinions regarding the local team. Together, these values allow us to compute all of the sufficient statistics defined in the previous section. We fit (2) using maximum likelihood estimation, and fit (3) using iterative stochastic approximation using the score function as outlined in [19]. Standard errors for all coefficients are derived from the information matrices at the final estimate. To determine model, we compute the deviance for a null model – intercept only – and the deviance for the model and compare.

C. Results

In Table 2 we present the results for the evolution of MTS identity. The dependent variable here is the state of each individual's feeling of identity, as predicted by prior communication activity and the feelings of others in the network. The activity rate variables are factors that influence how likely an individual is to make a change, regardless of direction. We find that when actors have high in and out-degrees, they are more likely have their feelings of MTS identity evolve (α=1.79, $p<0.001$; α=1.13, $p<0.001$). This finding suggests that exposure to more communication makes a person more willing to change. We also find that recon officers and field specialists (worker roles in the game) are more likely to change their opinions than leaders, which were set as the baseline (α=1.14, $p<0.001$; α=1.02, $p<0.001$). Finally, we find that individuals who hold a very high opinion are more likely to change that opinion than those with a low or average feeling of identity (α=1.03, $p<0.001$). In Table 2 we also present results for the change probability variables, which measure the likelihood of identity change in a positive or negative direction. We find that agents tend to adopt similar feelings of MTS identity to those whom they frequently talk to (communication assimilation; β=1.81, $p<0.001$) and those whom they share a team with (squad and fire-team assimilation; β=12.29, $p<0.001$; β=3.44, $p<0.001$). We also find that people who have the same function in the experiment (role assimilation) tend to have differing views of the MTS (β=–3.32, $p<0.001$). Finally, we see that there is no correlation between MTS identity and squad identity, or with feelings of interdependence.

In Table 3 we present the results for activity rate and change decision for MTS information interdependence. The outcome variable here is an individual's feeling of dependence on external sources for information, as predicted by prior communication and the opinions of others in the network. We find that when an individual receives a high volume of communication, they are less likely to change their opinion

TABLE II. Parameter estimates and standard errors for the evolution of MTS identity. Significance codes for the p-values are: *** $p < 0.001$, ** $p<0.01$, * $p<0.05$.

	DV: MTS Identity		
	Coefficient	***SE***	***p-value***
Activity Rate Parameters			
Constant	-3.71	0.06	***
In Degree	1.79	0.05	***
Out Degree	1.13	0.20	***
Covariate: Recon Officer	1.14	0.20	***
Covariate: Field Specialist	1.02	0.03	***
Positivity	1.03	0.03	***
Change Decision Parameters			
Positivity	5.01	12.67	
Communication Assimilation	1.81	0.57	***
Squad Assimilation	12.29	1.81	***
Fire-team Assimilation	3.44	0.96	***
Role Assimilation	-3.32	1.42	*
Squad Identity	0.08	1.40	
MTS Information Interdependence	0.16	2.45	
MTS Goal Interdependence	0.40	3.66	
Null Deviance	31,135		
Residual Deviance	22,153		

(α=–0.77, $p<0.001$), while those that send a high volume are more likely to change (α=1.47, $p<0.001$). Further, workers in the system are more likely to change than leaders (α=1.25, $p<0.001$; α=1.03, $p<0.001$). Finally, we find that those individuals with a high opinion are more likely to change their opinion over time (α=0.77, $p<0.001$). We next consider the results for the decision variables. First, we find that positivity is negative and significant (β=–14.61, $p<0.001$), indicating that over time, individuals tend to feel less dependent on other teams for information. Communication assimilation is also negative and significant (β=–1.44, $p<0.001$), suggesting that individuals tend to form opinions that are distinct from those they communicate with most frequently. Finally, we find that individuals tend to positively assimilate with members of their own squad (β=3.16, $p<0.001$), members of their fire-team within the squad (β=1.36, $p<0.001$), and others who perform the same role (β=3.42, $p<0.001$).

In Table 4 we present the results of the relational event model. Here, the outcome variable is future communication, predicted by prior communication patterns. For this study we focused on endogenous structural mechanisms, covariate effects related to the MTS hierarchy, and the similarities between individuals across a number of opinion measures. We

TABLE III. PARAMETER ESTIMATES AND STANDARD ERRORS FOR THE EVOLUTION OF MTS INFORMATION INTERDEPENDENCE. SIGNIFICANCE CODES FOR THE P-VALUES ARE: *** $p < 0.001$, ** $p<0.01$, * $p<0.05$.

	DV: Information Interdependence		
	Coefficient	***SE***	***p-value***
Activity Rate Parameters			
Constant	-1.61	0.09	***
In Degree	-0.77	0.10	***
Out Degree	1.47	0.20	***
Covariate: Recon Officer	1.25	0.23	***
Covariate: Field Specialist	1.03	0.03	***
Positivity	0.77	0.04	***
Change Decision Parameters			
Positivity	-14.61	7.36	
Communication Assimilation	-1.44	0.51	***
Squad Assimilation	3.16	0.58	***
Fire-team Assimilation	1.36	0.44	***
Role Assimilation	3.42	0.38	***
MTS Identity	0.99	0.66	
Squad Information Interdependence	2.86	1.24	*
MTS Goal Interdependence	-0.70	1.93	
Null Deviance	28,208		
Residual Deviance	22,608		

find evidence of a lack of centralization (preferential attachment not significant) and a lack of cyclical ties (ITP not significant; ISP $\theta=-116.58$, $p<0.001$). We do find evidence of some transitivity (OTP $\theta=5.95$, $p<0.001$; OSP $\theta=4.96$, $p<0.001$). The results for covariate effects indicate that individuals preferentially communicate with members of the same squad ($\theta=1.54$, $p<0.001$), members of the same fire-team ($\theta=0.20$, $p<0.001$), and others who share the same function ($\theta=1.00$, $p<0.001$). Finally, we find that members of an MTS tend to communicate more frequently with others who expressed similar opinions regarding MTS identity ($\theta=0.58$, $p<0.001$) and feelings of interdependence ($\theta=0.27$, $p<0.001$).

D. Discussion

A qualitative analysis of our findings leads to several interesting takeaways. First, we find that members of an MTS tend to feel a stronger sense of identity towards the system if the members of their local team do, and if the people with whom they communicate with do as well. These results suggest that peer influence, either through a formal team or through communication networks, significantly shapes an individual's view of their organization. The consequence of this pattern is that the tension between team and system may become greater if one team is out of sync with the MTS; this type of conflict meshes with the notion of countervailing forces [26]. We also

TABLE IV. PARAMETER ESTIMATES AND STANDARD ERRORS FOR THE RELATIONAL EVENT MODEL. SIGNIFICANCE CODES FOR THE P-VALUES ARE: *** $p < 0.001$, ** $p<0.01$, * $p<0.05$. $N = 3{,}114$ COMMUNICATION EVENTS.

	DV: Communication Event		
	Coefficient	***SE***	***p-value***
Structural Parameters			
Constant	-9.58	0.10	***
Persistence	3.76	0.07	***
Reciprocity	-1.90	0.16	***
Activity	9.98	0.21	***
Preferential Attachment	0.55	0.30	
OTP	5.95	0.54	***
ITP	-3.15	2.19	
OSP	4.69	0.93	***
ISP	-116.58	17.52	***
Fixed Effects			
Covariate: Shared Squad	1.54	0.04	***
Covariate: Shared Fire-team	0.20	0.07	***
Covariate: Shared Role	1.00	0.04	***
Exogenous Behavioral Effects			
Similarity – MTS ID	0.58	0.10	***
Similarity – Squad ID	-0.22	0.10	*
Similarity – MTS Info	0.27	0.08	***
Similarity – Squad Info	1.15	0.10	***
Similarity – MTS Goals	0.64	0.08	***
Similarity – Squad Goals	-0.89	0.07	***
Null Deviance	45,785		
Residual Deviance	37,781		

find that over time, individuals tend to communicate more frequently with those who hold similar opinions of the MTS, thus reinforcing their feelings. Second, we find that individuals tend to rely on other teams for information if their own local team does as well. However, if a person frequently communicates with individuals who feel dependent on other teams for information, that person tends to feel less dependent. A possible explanation concerns the flow of information in the experimental scenario. If an individual frequently talks with others who feel a strong information dependency, then that person may feel *relied upon*, or feel as if they are a source of information, rather than seeking it themselves. In this case, they may report feeling less dependent on other teams. This conclusion may be particularly true if the individual frequently communicates across team boundaries [27].

A third takeaway is that the psychological variables we studied through surveys tended to evolve independently of one another. Our models suggest that feelings of MTS identity are unrelated to feelings of information interdependence, and vice versa. We also included feelings of squad identity, squad-level information dependence, and goal alignment. The only significant relationship was between MTS and squad-level information interdependence. This result suggests that someone who feels dependent on their teammates for information to complete their tasks also feels dependent on other teams. A possible explanation is that certain roles within the system, such as reconnaissance officers, by nature require high levels of information. To confirm this, we would need to delineate the effect according to the role covariate.

These initial results highlight the opportunity for more nuanced study of team and multiteam system processes. In this setting, the joint dynamics of teamwork and the feelings of the team members themselves are crucial to predict the success of the organization. Further, given the increased access to digital trace data, the coordination and communication processes of a team can be observed in continuous time. Our method is thus an ideal choice for studying organizations when both relational event and psychological survey data are available.

IV. Conclusions

The methodology we present here is a novel integration of relational event modeling and stochastic actor-oriented models. This development is spurred by the increasing availability of timestamped digital trace data, which allows for continuous observation of network dynamics. However, it is still practically difficult to collect continuous data on the behavioral, cognitive, or emotional states of network actors. Therefore, the actor-oriented approach is useful for simulating individual-level dynamics. Our model therefore augments the predictive capabilities of relational event modeling, while preserving the functionality of well-defined SAOM's. The high granularity of the network data also allows for more stable simulations of the behavioral dynamics, as well as more intricate sufficient statistics.

Our empirical example illustrates the utility of our model for analyzing complex organizational systems that vary at multiple levels. In a multiteam system, individuals are embedded in both a team and a system of teams. Using our approach, we can determine the social forces that contribute to the evolution of identity and informational interdependence within an MTS. While the analysis presented here is exploratory, it does yield some interesting insights and is congruent with literature on MTS. The results suggest that our methodology is a promising tool for future organizational research.

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