Group Dynamics: Theory, Research, and Practice
2016, Vol. 20, No. 3, 223–241

1089-2699/16/$12.00 http://dx.doi.org/10.1037/gdn0000046

Using Recurrence Analysis to Examine Group Dynamics

Andrew P. Knight
Washington University in St. Louis

Deanna M. Kennedy
University of Washington Bothell

Sara A. McComb
Purdue University

This article provides an accessible introduction to recurrence analysis—an analytical approach that has great promise for helping researchers understand group dynamics. Recurrence analysis is a technique with roots in the systems dynamics literature that was developed to reveal the properties of complex, nonlinear systems. By tracking when a system visits similar states at multiple points in its life—and the form or pattern of these recurrences over time—recurrence analysis equips researchers with a set of new metrics for assessing the properties of group dynamics, such as recurrence rate (i.e., stability), determinism (i.e., predictability), and entropy (i.e., complexity). Recent work has shown the potential value of recurrence analysis across a number of different disciplines. To extend its use within the domain of group dynamics, the authors present a conceptual overview of the technique and give a step-by-step tutorial on how to use recurrence analysis to study groups. An exemplar application of recurrence analysis using dialogue-based data from 63 three-person student groups illustrates the use of recurrence analysis in examining how groups change their focus on different processes over time. This is followed by a discussion of variations of recurrence analysis and implications for research questions within the literature on groups. When group researchers track group processes or emergent states over time, and thus compile a time series dataset, recurrence analysis can be a useful technique for measuring the properties of groups as dynamic systems.

Keywords: group dynamics, group processes, recurrence analysis, recurrence plots, time-series data

There is a recurring pattern in the study of groups. Scholars propose new conceptual models that underscore the dynamism inherent to groups (e.g., Kozlowski, Gully, Nason, & Smith, 1999; Marks, Mathieu, & Zaccaro, 2001; McGrath, 1991; Tuckman, 1965). Shortly thereafter, commentaries lament the paucity of empirical research on group dynamics (e.g., Arrow, McGrath, & Berdahl, 2000; Cronin, Weingart, & Todorova, 2011; Kozlowski, Chao, Chang, & Fernandez, 2016; McGrath, 1986). Among the reasons cited by commentators for this persistent gap are limitations in the analytical tools group researchers are commonly taught and frequently employ. Ubiquitous in the group literature are statistical approaches directly or indirectly grounded in the general linear model—a model that, while powerful, brings inherent limitations for understanding change in groups over time. The general linear model, which aligns well with the input-process-output (I-P-O) conceptual model of groups (e.g., Hackman, 1987), treats activity in groups as a linear, delimited sequence of rela-

Andrew P. Knight, Olin Business School, Washington University in St. Louis; Deanna M. Kennedy, School of Business, University of Washington Bothell; Sara A. McComb, Schools of Nursing and Industrial Engineering, Purdue University.

This research was supported in part by the Collaboration and Knowledge Interoperability program of the Office of Naval Research (Grants N000140210535, N000140610031, N000140810986, and N000141110236) and the Innovations in Organizations program of the National Science Foundation (Grant 0092805). We are grateful to Giorgio Tasca for his constructive feedback on prior versions of this article.

Correspondence concerning this article should be addressed to Andrew P. Knight, Washington University in St. Louis, Campus Box 1156, One Brookings Drive, St. Louis, MO 63130. E-mail: knightap@wustl.edu

tionships. Although both the general linear model and the I-P-O model are useful and have greatly advanced scholarship about groups, these models may overly simplify the reality of group dynamics.

Recognizing the limitations of conceptualizing group activity as a single, delimited sequence of inputs, processes, and outputs, more recent conceptualizations portray groups as transitioning through several interlocked activity cycles. For example, Marks et al. (2001) argue that groups move through multiple performance episodes. Each performance episode is an I-P-O chain, with outputs of one episode serving as inputs to the next episode. Other recent models of group behavior (e.g., Ilgen, Hollenbeck, Johnson, & Jundt, 2005; Kozlowski & Ilgen, 2006; Mathieu, Maynard, Rapp, & Gilson, 2008) similarly characterize groups as moving through multiple cycles of activity over time. Yet, the general linear model—and the analytical mindset it provokes (Zyphur, 2009)—is ill-equipped to represent cycles of group activity over time, especially if those cycles contain feedback loops, recursion, or nonlinear dynamics.

The purpose of this paper is to highlight and demonstrate how to use a novel analytical approach—recurrence analysis—that is particularly amenable to studying groups as cycles of interlocked activity over time. Systems dynamics scholars developed recurrence analysis to assess and monitor changes in dynamic nonlinear systems (Eckmann, Kamphorst, & Ruelle, 1987). Initially a graphical approach used to illustrate patterns of recurrent activity in a system over time, recurrence analysis has advanced significantly over the past three decades (Marwan, 2008). Correspondingly, its use has grown dramatically, providing insights into a range of research domains, such as the dynamics of human conversations (Dale & Spivey, 2006; Richardson & Dale, 2005), the ebb and flow of labor markets (Caraiani & Haven, 2013), and the activity of the human heart (González, Infante, Pérez-Grovas, Jose, & Lerma, 2013).

Recurrence analysis is also a technique that researchers have begun using to examine coordination between pairs of people working together on a common task (e.g., Fusaroli & Tylén, 2016; Shockley, Santana, & Fowler, 2003; Strang, Funke, Russell, Dukes, & Middendorf, 2014), shedding light on both the conditions under which coordination emerges and the implications of different dynamic structures. Although few published studies have used recurrence analysis to study groups composed of more than two people (two exceptions are Fusaroli, Bjørndahl, Roepstorff, & Tylén, 2016 and Gorman, Cooke, Amazeen, & Fouse, 2012), it has great potential for illuminating new directions for theory and research on group dynamics (Fusaroli, Konvalinka, & Wallot, 2014). By providing an overview of recurrence analysis, along with a group-focused tutorial, we make the technique more accessible for group researchers and aid efforts to fill the gap in empirical research on group dynamics.

To highlight the potential value of recurrence analysis, we first identify limitations of four commonly used analytical approaches for studying group dynamics. Then, we give a brief historical background of recurrence analysis, including an account of its conceptual foundations, and discuss recent applications for understanding coordination. Next, we provide a step-by-step demonstration of how time-series data and recurrence analysis can be used to examine group dynamics. We conclude by discussing variations of recurrence analysis and broader implications for researchers who study groups.

Four Common Analytical Approaches to the Study of Groups

Four basic analytical approaches are prevalent in group research. Each one makes important assumptions that may limit researchers seeking to study groups as interlocked cycles of activity over time. To illustrate the approaches and their limitations, consider a fictitious study where groups completed a 1-hr laboratory task and a researcher used observational methods to rate group mood (i.e., the degree to which group interactions are characterized by positive and negative emotions) and information sharing (i.e., the degree to which members exchange unique information) on a minute-by-minute basis. The fictitious time-series dataset thus consists of 60 ratings of mood and information sharing for each group.

The first common approach that researchers use to examine this type of data is to *aggregate* the potentially dynamic ratings of focal constructs across time. The assumption underlying this approach is that, at least for the observation period, the constructs of interest are not changing meaningfully. For the fictitious dataset, this aggregation would lead to a single mood score and a single information sharing score per group, each represented by the average value across the study period. While this approach enables studying relationships among constructs (e.g., information sharing and mood), aggregating observations over time precludes addressing research questions that focus on dynamics, such as how mood and information sharing might change over time as a function of temporal milestones or other emergent states.

The second common approach used to examine time-series data is to *separate* construct measurements across time, thereby ignoring any potentially meaningful linkages attributable to the temporal sequence in which they occur. With this approach, researchers focus specifically on the co-occurrence or direct causal relationship between two variables, rather than on changing patterns over time. For the fictitious example, the relationship of interest might be between information sharing and mood at various points in time. This approach, which eliminates the temporal structure of the data (or vastly simplifies it), is often used in experience sampling studies (e.g., Totterdell, Kellett, Teuchmann, & Briner, 1998). As with aggregating data, this approach precludes addressing research questions focused on group dynamics.

The third approach is to *describe* patterns of change over time using qualitative methods. For the fictitious example, a researcher might observe sequences of mood or information sharing in a small number of groups and use qualitative data to develop theory about how mood and/or information sharing change over time. A descriptive approach has yielded significant insights into group dynamics, serving as the basis for some of the most impactful models of development and change over time in the group literature (e.g., Bales, 1950; Gersick, 1988; Tuckman, 1965). This approach, however, is infeasible for deductive research using large datasets. Instead, it is most useful for inductively generating insights into group dynamics.

The fourth approach, which group researchers are using with increased frequency, is to *linearize* the trajectories of change in focal constructs over time and use multilevel modeling (e.g., Knight, 2015; Mathieu & Rapp, 2009) or structural equation modeling (e.g., Edmonds, Tenenbaum, Kamata, & Johnson, 2009; Tasca & Lampard, 2012) to estimate a variety of longitudinal models (e.g., latent growth curve, latent change score analysis). Although these models are flexible, and can test complex and reciprocal relationships, a key assumption that underlies these models is that change trajectories are the product of linear processes. In other words, researchers using these models must assume that the error terms in their models are independent—what causes one variable to change does not interact with what is causing another variable to change. Importantly, this issue is not one of fitting curvilinear change trajectories, which is indeed possible (e.g., adding a quadratic term to represent curvilinear change). Rather, this issue references the kinds of processes that are assumed to underlie the dynamics being studied. Beyond this important assumption, these longitudinal models generally require researchers to reduce the complexity of a temporal dataset to fit relatively simple patterns of change over time. For the fictitious example, a researcher would likely aggregate the 60 min-level data points into four to six phase-level data points to fit a linear, quadratic, or cubic trajectory. Accordingly, although using multilevel or structural equation modeling enables researchers to study dynamics, using these models requires reducing the true complexity of change and assuming linear dynamics—an assumption that may be untenable in group research.

In sum, the analytical approaches commonly used to study groups require that researchers adopt a relatively simplistic view of the processes that underlie group dynamics. These approaches lead researchers to ignore change, to describe change qualitatively, or to assume that change is the product of linear, rather than nonlinear, dynamics. Below, we describe recurrence analysis, an analytical approach that can address these limitations and complement existing analytical tools in group research. Rather than imposing linear dynamics on time-series data, recurrence analysis provides researchers with a way to assess the dynamic nature of groups and, thus, offers a novel lens through which to view group dynamics.

Recurrence Analysis

Background and Conceptual Introduction

Recurrence analysis was originally designed as a graphical technique for making sense of complex system dynamics (Eckmann et al., 1987). Having roots in complexity theory—a tradition with a strong predilection for visualizing data to reveal the key features of nonlinear systems (Gleick, 1997)—recurrence analysis began as a sophisticated plot illustrating system properties. Called a *recurrence plot*, the principle guiding Eckmann and his colleagues' thinking in developing this visualization was that seeing how a dynamic system recurs—how it revisits similar states at different points in time—might help shed light on its core properties. Early recurrence plots revealed, for example, the unique patterns of recurrence that classic nonlinear systems, such as the Lornez and Henon systems, make (see Gleick, 1997 for an accessible overview of nonlinear dynamics, including the properties of these classic systems). By providing a way to quantify the properties of dynamic systems, recurrence analysis offers group researchers a new approach for empirically studying group dynamics. Rather than presuming that such systems are linear, researchers can use recurrence analysis to assess the degree to which a system is, for example, stable, predictable, and complex.

Before discussing the mechanics of recurrence analysis, we first illustrate its conceptual foundations using the example of a simple dynamic system—a train that runs along a West-to-East track with 10 stations, stopping every 10 minutes at the next station in sequence. When the train reaches the end of the line, it reverses course and continues running. A time-series dataset containing two variables—time and the location of the train—could be used as the basis of a recurrence plot. Figure 1A displays a standard time-series plot for a typical day, in which the train runs between 5 a.m. and 11 p.m. The *x*-axis in Figure 1A represents time of day and the *y*-axis represents the location of the train. Figure 1B displays a recurrence plot of the same data. In the recurrence plot both axes now represent time of day. A dot in Figure 1B indicates two points in time when the train is at the same station. Which specific station is not specified in the recurrence plot; however, the pattern of dots immediately reveals the periodic and deterministic nature of the dynamic system. Note that a recurrence plot of a single system—sometimes called an autorecurrence plot—is symmetric across the diagonal. Further, the diagonal in a plot of a single system will always be marked as recurrent. This simple example illustrates the key building block of recurrence analysis—the idea that marking when a system is in the same state at two points in time sheds light on the nature of its dynamics.

As this example shows, a recurrence plot can be constructed to represent the dynamics of a single system across a delimited period of time. Using the plot, researchers can derive metrics that represent various properties of the system. This extension of the plot is called *recurrence quantification analysis*. The evolution of social network analysis is a useful analogy for understanding this extension of recurrence plots. Initial social network research relied on network graphs—visual displays of nodes (e.g., people) and edges (e.g., friendship ties). Contemporary network research, however, uses sophisticated metrics that quantify properties of network graphs (Wasserman & Faust, 1994). Like quantifying networks, quantifying recurrence plots is useful because it facilitates studying several groups to test predictions about how and why groups differ from one another in their dynamics. Using metrics from recurrence quantification analysis applied to multiple recurrence plots (i.e., one plot per group), researchers can operationalize properties of group dynamics—such as the propensity of the system to recur or how deterministic the system is—and use the values in subsequent analyses. We describe in detail below three measures based on recurrence plots that may be particularly relevant for researchers who study group dynamics. Before doing so, however, we share three examples of how researchers have recently used recurrence analysis to understand interpersonal dynamics.

Using Recurrence Analysis to Study Interpersonal Dynamics

To begin illustrating how recurrence analysis provides group researchers with a novel perspective on group dynamics, we review how three recent articles used recurrence analysis to understand the dynamics of interpersonal interactions among people engaged in cooperative tasks.

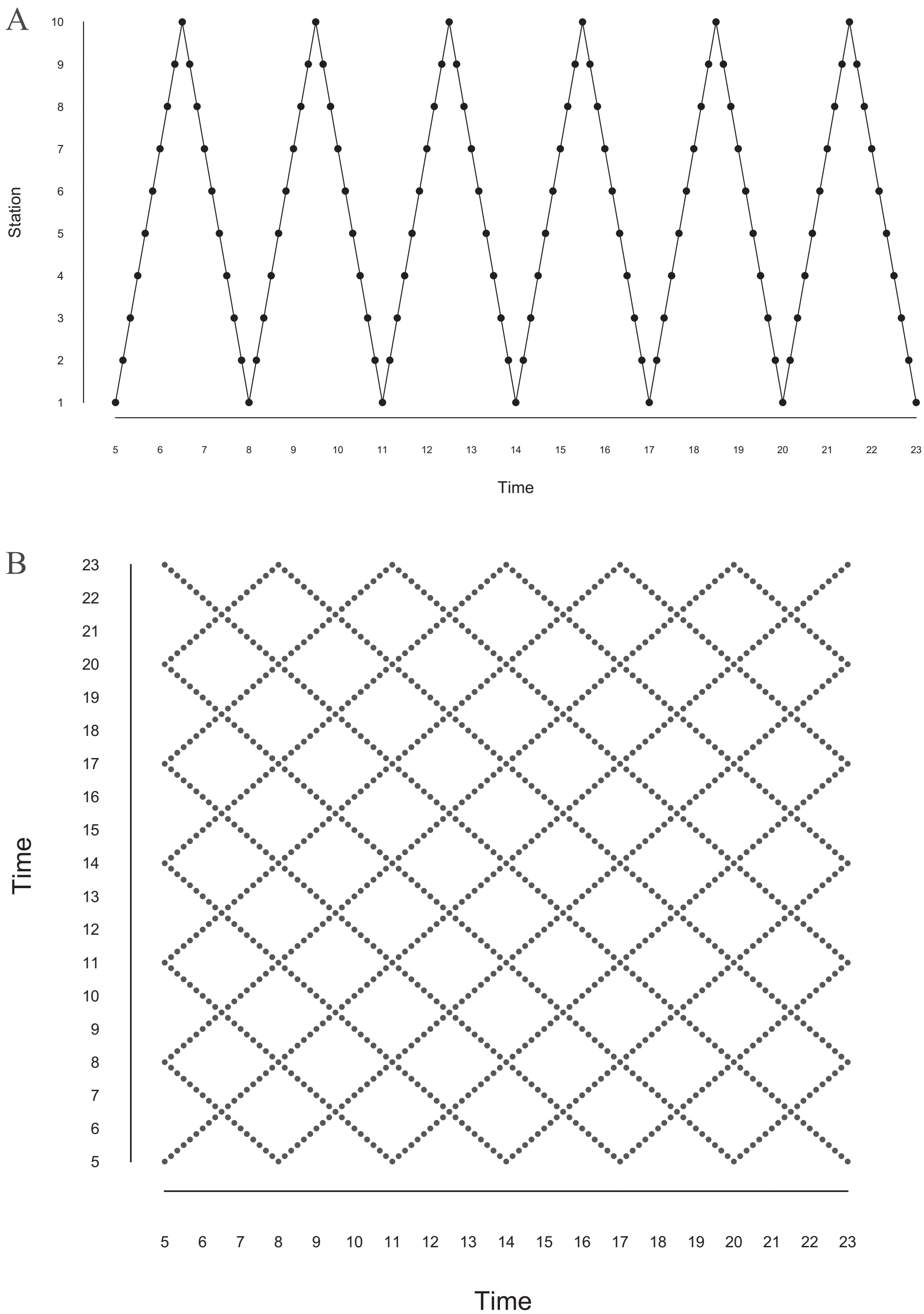

Figure 1. Plots of a fictitious train system. (A) Traditional time-series plot. (B) Recurrence plot.

These articles show how the metrics derived from recurrence analysis can be used in different ways to assess the nature of group dynamics. And these articles show how recurrence analysis can be integrated with a researcher's existing analytical toolset (e.g., general linear model) to test theoretically meaningful questions about group dynamics. Table 1 summarizes key aspects of how these selected articles use recurrence analysis to study interpersonal dynamics.

First, Gorman et al. (2012) used recurrence analysis to understand how communication dynamics differ among the members of three-person groups that retain stable membership across performance episodes, compared to those that change membership across performance episodes. Gorman et al. (2012) collected communication patterns among group members operating uninhabited air vehicles using the recordings of push-to-talk devices that marked which group member communicated at a given point in time and the target of communication (i.e., either or both of the other group members). The sequence of communications thus provided a time-series dataset recording the communication state of the group over time. Gorman et al. (2012) used recurrence quantification analysis to measure how structured or patterned the communication dynamics in groups were. Integrating recurrence-based measures into subsequent analyses showed that communication dynamics tended to increase more in predictability across performance episodes in intact groups than in groups that experienced membership change. Gorman et al.'s (2012) analyses illustrate the potential value of recurrence analysis for assessing how predictable, or deterministic, communication dynamics are in groups—a characteristic that is likely associated with aspects of coordination that are of interest to group researchers.

Second, Strang et al. (2014) used a variation of recurrence analysis—cross recurrence analysis—to examine questions about coordination and performance in dyads engaged in a cooperative video game task. As we discuss in greater detail below, cross recurrence analysis is a variant of recurrence analysis that examines the dynamic interplay of two systems—in this case, of two people—over time. Strang et al. (2014) used metrics from cross recurrence analysis to measure the degree of coupling, or synchrony, in dyad members' physiology (i.e., cardiac interbeat intervals) and behavior (i.e., postural sway). By comparing the dynamics of a true dyad (i.e., two people who did work together) to that of a random dyad (i.e., two people who did not work together), Strang et al. (2014) showed that coupling emerges during collective work. Further, the authors related recurrence metrics to survey measures (e.g., cohesion) and performance, providing evidence for the benefits of complementary coupling. Strang et al.'s (2014) results show the value of using nonlinear methods like recurrence analysis for assessing within-group coupling—a phenomenon that also is likely associated with coordination in groups.

Third, Fusaroli and Tylén (2016) used both recurrence analysis and cross recurrence analysis in a study of dyadic conversational dynamics and performance on a joint decision-making task. They created time series datasets with attributes representing three different characteristics of conversation between dyad members (i.e., lexical choice, prosody, speech/pause rhythm). The authors used recurrence analysis to assess the structural organization of conversation over time. By using recurrence analysis on (a) the conversation stream of the dyad as a whole, (b) on the dialog from each individual member, and (c) cross recurrence analysis of the dyad's conversation, Fusaroli and Tylén (2016) were able to test nuanced hypotheses about how conversation dynamics relate to dyadic performance. Results suggested that synergistic conversational patterns (e.g., complementarity) best predict dyadic performance. As with the examples above, their findings illustrate the potential value of recurrence analysis as a way to measure the dynamics of coordination, in this case with a focus on dyadic dialogue.

These three selected examples suggest a range of ways that recurrence analysis can be used to assess the nature of group dynamics in novel and theoretically meaningful ways. Of greatest relevance for group researchers, these studies suggest that recurrence analysis can provide a package of metrics for assessing the dynamic structure of group activity, which might then be related to other group attributes and outcomes.

Illustrative Application and Tutorial

To further illustrate the potential value of recurrence analysis for studying group dynamics, as well as to show specifically how to conduct recurrence analysis, we provide an exemplar application and step-by-step tutorial focused on groups.

Table 1
Three Sample Articles That Use Recurrence Analysis to Understand Interpersonal Dynamics

Study	Sample	Research question	Data sources	Use of recurrence analysis	Decisions in using recurrence analysis	Key findings
Gorman et al. (2012)	135 people working in three-person teams charged with flying uninhabited air vehicles across a series of missions	How does team coordination differ between teams that change membership (mixed teams) versus teams that do not (intact teams)?	Discrete communication turntaking as recorded by push-to-talk devices.	Analysis type: RQA Measures used: Determinism	Embedding: No Time lag: No Threshold: 0	Intact teams showed increased determinism across missions, indicating less flexibility (more structure) in communication than mixed teams.
Strang et al. (2014)	80 people, with 40 working in pairs and 40 working alone on a cooperative video game task	Do team members' physiological and behavioral patterns become coupled during a performance event? How does coupling relate to team characteristics and performance?	Continuous recordings of ECG measurements for cardiac IBI and continuous eye tracking for PS. Also assessed team characteristics and performance.	Analysis type: CRQA Measures used: Recurrence rate, entropy Windowing: IBI = 5 min with 2.5 min overlap; PS = 1 min with 30 s overlap	Embedding: Yes: IBI = 6; PS = 10 Time lag: Yes: IBI = 4; PS = 6 Threshold: IBI = 4; PS = 8 (using Euclidean rescaling)	Physiobehavioral coupling was more likely than chance and had a negative relationship with team performance. This may be due to complementary coordination rather than the mimicry that occurred due to different roles.
Fusaroli & Tylén (2016)	32 people working in pairs on a joint decision making task	What is the link between the structural organization of conversation in terms of interpersonal synergy, interactive alignment or self consistency and functional efficiency?	Communication transcripts between partners coded into discrete speech-pause sequences.	Analysis type: RQA and CRQA Measures used: Average diagonal line length, Entropy (from both RQA and CRQA) to assess self consistency and interpersonal synergy and alignment	Embedding: Yes, varied per dyad Time lag: Yes, varied per dyad Threshold: Varied per dyad	Greater interpersonal synergy was positively associated with dyad performance; the higher the entropy of transcript and frequency, or the greater the average line length of speech/pause then the better the performance.

Note. RQA = recurrence quantification analysis; CRQA = cross recurrence quantification analysis; IBI = interbeat intervals; PS = postural sway.

In this tutorial we (a) highlight the major decision points involved in conducting recurrence analysis, (b) specify three metrics derived from a recurrence plot especially useful for group researchers, and (c) illustrate how recurrence analysis can address novel questions in the study of group dynamics. Several software packages, spanning computing environments, exist for conducting recurrence analysis (for an updated listing, see http://www.recurrence-plot.tk/). For this tutorial, we directly calculated metrics using the formulas below and the open source software environment R.

As a first and prerequisite step, a researcher must formulate a research question that addresses group dynamics. Formulating this question requires drawing from existing theories and frameworks, perhaps adapting these to develop hypotheses about groups as dynamic systems that fluctuate over time. In this exemplar application, we draw from Marks et al.'s (2001) recurring phase model of groups, which suggests that groups engage in transition processes (e.g., planning, strategy formulation) and action processes (e.g., monitoring goal cycles) and, further, that cycles of transition and action processes recur.

To illustrate a novel use of recurrence analysis, we examine whether two contextual factors might influence the dynamic structure of a group's pattern of processes over time. In particular, we focus on how the dynamic structure of group processes may depend on (a) the medium through which group members communicate (face-to-face vs. computer-mediated) and (b) whether group members are working together on a task for the first time (vs. a second time). Because it offers the possibility to transmit more information, we expect that groups' dynamic structure will be more predictable and complex when members communicate face-to-face than via computer. Further, because group members working together for a second time already had the opportunity to learn and develop routines, we expect that the dynamic structure of group processes will be more predictable and complex in groups' second performance episode, compared to their first. Recurrence analysis facilitates examining these questions by providing a way to assess dynamic structure.

The second step in using recurrence analysis is to collect time-series data. Here the researcher must decide on the variable(s), measurement approach(es), measurement rate(s), and time window for data collection. For this exemplar application, we used discrete time-series data from 63 three-person groups that each completed two episodes of an intellective laboratory task requiring them to solve a personnel scheduling problem (Kennedy & McComb, 2014). Groups were randomly assigned to one of two conditions—(a) a face-to-face condition, in which group members met and interacted in person to complete their task, and (b) a computer-mediated condition, in which group members met and interacted through a computer platform to complete their task. Group processes were assessed over time by coding transcriptions of communications among group members. Each discrete message in the flow of group conversation was assigned one of five codes, derived from Marks et al.'s (2001) framework: (a) *mission analysis*, the formulation of task objectives, resources, and work parameters; (b) *tactical strategy*, the approach for task execution; (c) *operational strategy*, the approach to work allocation; (d) *goal specification*, the prioritization of task goals; and (e) *action processes*, those activities involved in performing the task. This process yielded a series of discrete codes for each group, such as ". . . (mission analysis) (mission analysis) (action) . . .," that reflects the message-to-message progression of group processes across a performance episode.[1] In addition to these group process codes, groups have a condition code (0 = computer mediated, 1 = face to face) and a performance episode code (0 = first episode, 1 = second episode).

The third step in a recurrence analysis is to transform the time-series data for each group—the ordered vector of group states over time—into a recurrence plot. It is important to note that each performance episode for each group is treated as a distinct dynamic system. As such, there is a distinct time series vector for each group-episode and a distinct recurrence plot, yielding a total of 126 plots for this sample dataset. The plot is based on transforming the time series vector into a recurrence matrix, $R_{i,j}$, which is a matrix of 1s and 0s that indicates when a system revisits a previous state. In this example, because our data comprised a single

[1] For more detail on the method and coding procedures, see Kennedy and McComb (2014).

vector of discrete states, the recurrence matrix denotes when a group was engaged in the same process at two points in time. Equation 1 below specifies that a 1 is assigned when a group process (e.g., mission analysis) is revisited at another point in time; otherwise, a 0 is assigned.

$$R_{i,j} = \begin{cases} 1 : x_i = x_j \\ 0 : x_i \neq x_j \end{cases} i, j = 1, \ldots N, \qquad (1)$$

where N is the number of messages in the transcript and x represents the group process code at message number i (or j). Figure 2 provides plots for four sample groups. Visually, the plots suggest that these groups progressed through two phases of activity, with a transition at roughly the midpoint of the communication transcripts. The plots suggest that groups revisited processes more during the second half of a performance episode than during the first half.

Inspecting recurrence plots is informative; however, it is difficult to derive precise conclusions from many plots—in this example more than a hundred. Accordingly, the fourth step in recurrence analysis is to derive standardized metrics that assess the dynamic structure depicted in each plot using recurrence quantification analysis. We detail here the equations behind three metrics that are useful for assessing how predictable and complex a dynamic struc-

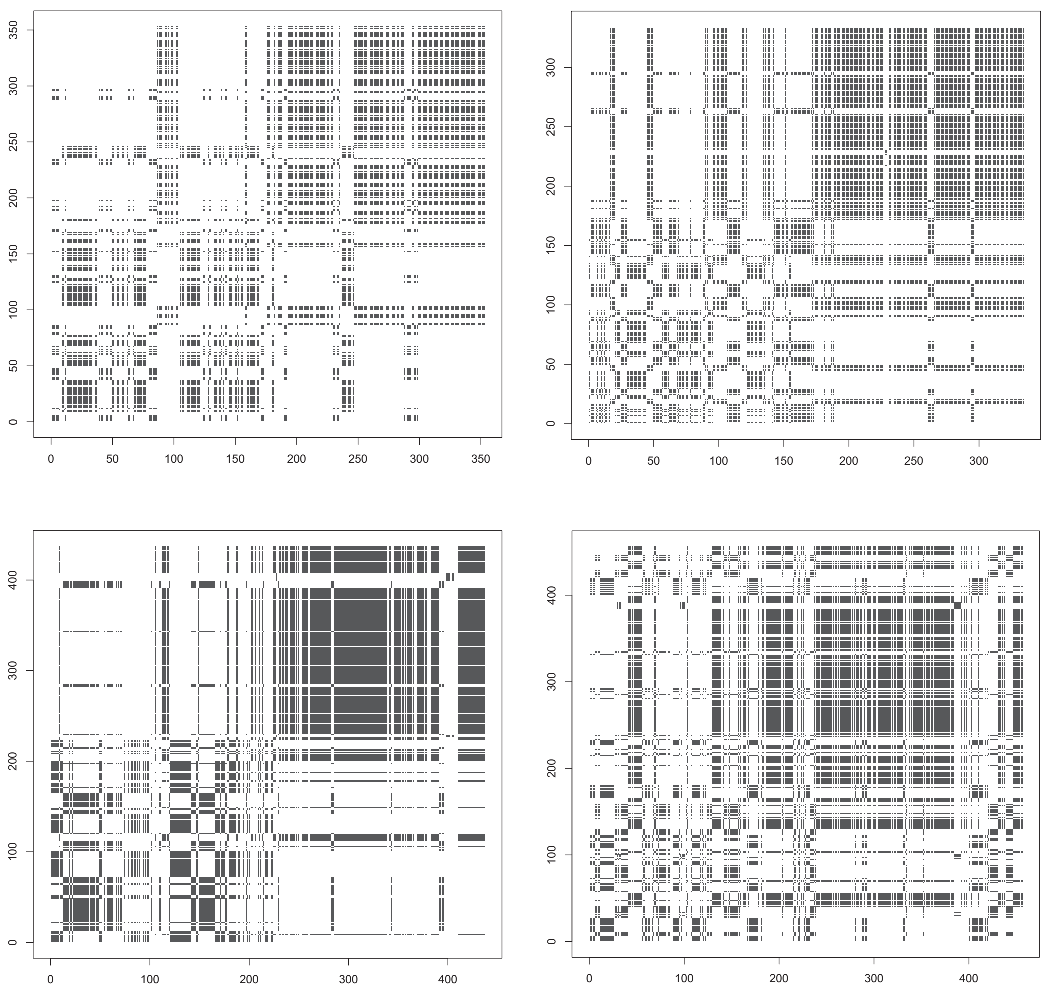

Figure 2. Recurrence plots for four group performance episodes.

ture is. Readers interested in other recurrence metrics should consult Marwan, Carmen Romano, Thiel, and Kurths' (2007) comprehensive review of recurrence analysis.

The first measure—*recurrence rate*—assesses how intensely a system revisits past states and reflects the density of recurrences in the plot. The recurrence rate is the proportion of points in the plot that are recurrent states; that is, the proportion of the plot that is filled with black dots. Equation 2 details the calculation of recurrence rate, which excludes the intrinsically recurrent data points along the main diagonal of the plot. Across the 126 performance episodes in the sample (63 groups with 2 episodes each), the mean recurrence rate is 53.61 ($SD = 15.26$), indicating that groups, on average, revisit one of the coded processes a little more than half of the time during a single performance episode.

$$RR = \frac{1}{N^2}\sum_{i,j=1,\, i\neq j}^{N} R_{i,j} \tag{2}$$

The second measure—*determinism*—is based on the arrangement of the points in the recurrence plot and reflects the degree to which system dynamics are predictable (i.e., deterministic). Determinism is evident in the presence of diagonal line structures in the plot that run parallel to the main diagonal (Webber & Zbilut, 1994). These upward-running diagonal lines mark periods when the system moves through a series of identical states over time. Consider again the train example depicted in Figure 1B. This plot has many long diagonal lines because the train system operates on a predetermined schedule. A plot containing few diagonal lines, in contrast, would suggest a more random dynamic process underlies the system. Determinism is commonly operationalized as the proportion of recurrent points in the plot that lie in a diagonal parallel to the main diagonal (Marwan et al., 2007; Webber & Zbilut, 1994). Calculating determinism requires first deciding how many points are needed to constitute a line; this is called the minimal line length, $l_{\min}$ (Marwan et al., 2007). The data about l are then organized into $P(l)$, a frequency distribution. As Equation 3 shows, determinism is the ratio of recurrent points found in a diagonal line of at least $l_{\min}$ to the total number of recurrent points.

$$\mathrm{DET} = \frac{\sum_{l=l_{\min}}^{N} lP(l)}{\sum_{i,j=1,\, i\neq j}^{N} R_{i,j}} \tag{3}$$

For this example, we set the minimal line length to three recurrent data points ($l_{\min} = 3$), indicating periods when groups were focused on the same process for at least three messages. Determinism was high in this study ($M = 89.80$, $SD = 9.03$), with nearly 90% of recurrences typically falling in a diagonal line of three or more points.

The third measure—*entropy*—provides an indication of the complexity of the system's deterministic structure (Webber & Zbilut, 1994). An entropy measure derived from a recurrence plot is based on the distribution of the upward sloping diagonal line lengths (i.e., lines parallel to the main diagonal; Marwan et al., 2007) and reflects Shannon entropy. The train example described above and depicted in Figure 1B has a very simple deterministic structure—the train stops at stations in sequence every 10 min—and, thus, has low entropy. This is reflected in the fact that the diagonal lines in Figure 1B are of relatively uniform length. A plot with diagonal lines of many different lengths, in contrast, would indicate high entropy and a complex deterministic structure. Calculating entropy requires creating a probability distribution of diagonal line lengths, $p(l)$. Then, as detailed in Equation 4, entropy is calculated as the Shannon entropy of the likelihood of a diagonal line being a given length in the plot. In the sample dataset, average entropy was 2.74 ($SD = 0.55$).

$$\mathrm{ENTR} = -\sum_{l=l_{\min}}^{N} p(l) \ln p(l) \tag{4}$$

The fifth step in recurrence analysis is to examine focal research questions by relating recurrence metrics to other variables, such as contextual factors, group attributes, and outcomes. In this example, we sought to examine how two contextual characteristics—communication medium and performance episode—relate to the dynamic structure of group processes. We also examined the relationship between recurrence metrics and group performance on the personnel scheduling task. Table 2 provides descriptive statistics and intercorrelations among recurrence metrics and other

Table 2
Descriptive Statistics and Intercorrelations Among Variables in Exemplar Application

Variable	*M*	*SD*	1	2	3	4	5	6	7
1. Session number	.50	.50							
2. Interaction medium	.44	.50	.00						
3. Number of messages	230.14	138.53	−.25	−.04					
4. Minutes working	61.30	25.29	−.51	−.35	.42				
5. Recurrence rate	53.61	15.26	.28	.36	.18	−.24			
6. Determinism	89.80	9.03	.24	.28	.28	−.09	.71		
7. Entropy	2.74	.55	.23	.16	.45	.02	.69	.70	
8. Cost of schedule	2,763.41	315.07	−.81	−.13	.18	.41	−.29	−.33	−.23

Note. $N = 126$ performance episodes nested within 63 unique teams. For Session number, first episode = 0, second episode = 1. For Interaction medium, computed mediated = 0 and face-to-face = 1.

variables. Because recurrence attributes might be associated with the length of time that group members worked together or to the total volume of communication among group members, we include these variables in Table 2 and in our further analyses. The pattern of bivariate correlations suggests, in line with our expectations, that the dynamic structure of group processes was more predictable and complex in face-to-face groups (compared to computer-mediated) and in groups engaged in their second performance episode (compared to their first).

To examine our research questions more precisely, we tested these relationships using multilevel models (Gelman & Hill, 2007), which account for the fact that performance episodes in our dataset are nested within groups. In these models we controlled for the amount of time (in minutes) that group members worked on a given episode and for the volume of their communication (in number of messages) and grand mean centered continuous predictors. Table 3 presents the results of models predicting the recurrence metrics described above. As expected, groups engaged in face-to-face communications had a higher recurrence rate ($B = 10.57$, $p < .01$), determinism ($B = 5.75$, $p < .01$), and entropy ($B = 0.24$, $p < .01$) than did groups engaged in computer-mediated communications. And groups in their second performance episode had a higher recurrence rate ($B = 9.66$, $p < .01$), determinism ($B = 6.45$, $p < .01$), and entropy ($B = 0.24$, $p < .01$) than did groups in their first performance episode. Table 4 relates these metrics to group performance, which for this task means producing a *lower* cost schedule. Model 1 of Table 4 shows that face-to-face groups performed better than computer-mediated groups ($B = -102.85$, $p < .05$) and that groups performed better in their second episode than

Table 3
Results of Multilevel Models Predicting Recurrence Metrics

Variable	Recurrence rate	Determinism	Entropy
Intercept	44.08 (2.38)	84.01 (1.38)	2.41 (.08)
Number of messages	.03 (.01)**	.02 (.01)**	.00 (.00)
Minutes working	−.04 (.06)	.02 (.04)	.00 (.00)
Session number	9.66 (2.47)**	6.45 (1.66)**	.44 (.10)**
Interaction medium	10.57 (2.89)**	5.75 (1.54)**	.24 (.09)**
Intercept	7.18	.00	.03
Residual	10.98	7.81	.45
AIC	1,011.24	891.84	200.00
Deviance	995.24	870.47	150.04

Note. $N = 126$ performance episodes nested within 63 unique teams. AIC = Akaike information criterion. Entries are unstandardized coefficients and (standard errors). For Session number, first episode = 0, second episode = 1. For Interaction medium, computer mediated = 0 and face-to-face = 1.
** $p < .01$.

Table 4
Results of Multilevel Models Predicting Cost of Schedule

Variable	Model 1	Model 2
Intercept	3,079.66 (32.48)	3,414.66 (180.10)
Number of messages	−.01 (.13)	−.01 (.15)
Minutes working	−1.14 (.87)	−.98 (.87)
Session number	−541.09 (34.58)**	−532.50 (38.16)**
Interaction medium	−102.85 (39.09)*	−88.50 (40.71)**
Recurrence rate		.87 (1.70)
Determinism		−6.02 (2.67)**
Entropy		54.32 (47.25)
Intercept	91.49	84.89
Residual	154.66	155.71
AIC	1,646.10	1,631.41
Deviance	1,656.28	1,650.79

Note. N = 126 performance episodes nested within 63 unique teams. AIC = Akaike information criterion. Entries are unstandardized coefficients and (standard errors). For Session number, first episode = 0, second episode = 1. For Interaction medium, computer mediated = 0 and face-to-face = 1.
* $p < .05$. ** $p < .01$.

their first ($B = -541.09$, $p < .01$). Model 2 of Table 4 shows that, with all three focal recurrence metrics in a regression model, a more deterministic dynamic structure was associated with the production of a lower cost schedule ($B = -6.02$, $p < .05$). This indicates that, at least for an intellective task such as this personnel scheduling one, more predictable group dynamics, reflected in higher determinism, are associated with better group performance. Conversely, groups performed poorly when their process dynamics were unpredictable. These results suggest that more predictable group dynamics, which are likely a reflection of effective coordination, may facilitate the execution of intellective problem-solving tasks.

Note that although neither the recurrence rate nor entropy were significant predictors in the multivariate regression model, each of these metrics had a bivariate relationship with cost of schedule that was similar to that of determinism (i.e., −0.29 for recurrence rate and −0.23 for entropy). The nonsignificance of these metrics in the regression model likely reflects their covariance with the relatively stronger predictor, determinism. Each metric has the presence of recurrences as its building blocks (i.e., the metrics share a common input) and, as such, the metrics are relatively highly correlated with one another.

This tutorial illustrates the potential of recurrence analysis for examining group dynamics in novel ways. The results of our illustration, along with studies of interpersonal dynamics (e.g., Fusaroli & Tylén, 2016; Shockley et al., 2003; Strang et al., 2014), show that the metrics derived from recurrence analysis are related to contextual factors and group outcomes.

Variations and Extensions

Our illustration of recurrence analysis thus far has intentionally highlighted its simplest foundations to give readers an introduction to its basic mechanics. As alluded to above, however, there are a number of important variations of and extensions to recurrence analysis. We highlight here those that are likely most relevant for groups researchers. Accounts of additional variations and issues to consider can be found in Marwan et al. (2007) and Fusaroli et al. (2014).

Variations. Our illustrative application and tutorial relied on a time-series dataset comprising discrete states. Similar to our example of a train running West-to-East, which stops in a series of discrete stations, our tutorial treated groups as moving discontinuously through a series of discrete processes (e.g., mission analysis, action processes). Both of these examples could, however, have used continuous indicators. The train location, for instance, could have been measured as kilometers from the origin station. Or, a group's state could have been measured using a continuous indicator of how much a group was engaged in a particular activity. Such operationalizations of group states using continuous indicators are very common in group research. Fortunately, recurrence analysis can easily accommodate continuous data. As detailed in Table 1, two of the three selected studies reviewed above—Strang et al. (2014) and Fusaroli and Tylén (2016)—used recurrence analysis with continuous indicators of a system's state over time. Using continuous data, however, introduces a complication to recurrence analysis—what is the threshold for marking an event as recurrent? That is, how close should two states be in the life of the system to be considered recurrent? Scholars have suggested a number of different approaches for deciding how to set this parameter, which is called the *recurrence threshold* or the *radius*. The decision, fundamentally, depends on the specific questions that a researcher is trying to answer with recurrence analysis (Marwan et al., 2007). Marwan (2011) provides a useful discussion of the factors to consider when choosing a threshold for recurrence analysis.

A second variation in conducting recurrence analysis that we have thus far overlooked is phase-space embedding. Phase space is a concept in physics that reflects the multiple dimensions that are needed to truly represent a dynamic system at a given point in time. In the train example above, only one dimension was used to reflect the state of the system—its location. However, the true state of the train at any given point in time comprises many more dimensions. The train is at a given altitude, for example, and is traveling at a given speed. While a researcher may measure only one dimension of a system over time (e.g., a focal process or emergent state), it is possible to represent the system in many more dimensions using what is called phase-space embedding. A major development in systems dynamics occurred when Takens (1981) showed that one could use a single dimension of a system to embed the system in phase space through time-delayed embedding. Time-delayed embedding entails unfolding a single time-series into multiple time-lagged dimensions. Conducting phase-space embedding involves making a number of additional decisions, such as selecting the most appropriate time lag and the number of dimensions needed to adequately represent the system. Because the choice of these parameters can influence recurrence metrics (Marwan, 2011), readers should consult Webber and Zbilut (2005) and Marwan et al. (2007) for detailed guidance on decision criteria.

Extensions. Our tutorial of recurrence analysis above illustrates one particular kind of recurrence analysis—called autorecurrence analysis because it is an analysis of the recurrence of a single system's state. We illustrated this type of recurrence analysis because it is the foundation upon which several extensions of recurrence analysis are built. We highlight here three extensions to this basic recurrence analysis that enable researchers to (a) examine the interplay of two systems, and (b) understand how dynamic structure might, itself, change over time.

Cross recurrence analysis, which we alluded to above, was developed to address questions regarding the degree to which the dynamics of two systems—two groups or two members of a single group, for example—converge and diverge over time. Considering the train example above, cross recurrence analysis would chart the progression of two trains, marking when one train visited a station that the other had also visited. Because cross recurrence analysis focuses on two systems, two time-series datasets are necessary. We described above Strang et al.'s (2014) research on physiological and behavioral coupling among dyad members engaged in a video game task. Each dyad member generates a time-series dataset, recording his or her state over the course of time. Rather than charting a single person's state against itself at different points in time (i.e., autorecurrence), cross recurrence analysis charts one person's state against the other's over time, marking when one person is in the same state as the other is or has been. Cross recurrence plots retain the same properties of basic autorecurrence plots and can be similarly quantified. The metrics that stem from a cross recurrence plot, however, reflect shared system properties, such as synchronization or entrainment. Cross recurrence analysis offers tremendous potential for understanding group dynamics. Researchers could use this technique on internal group dynamics to understand why some group members converge more than others or on external group dynamics to understand how a group becomes entrained to external factors. Two articles that provide a focused introduction to the use of cross recurrence analysis are Fusaroli et al. (2014) and Coco and Dale (2014).

Joint recurrence analysis is a mix of autorecurrence analysis and cross recurrence analysis. In joint recurrence analysis, a researcher first charts the recurrences of a single system, then repeats this process with a second system. The two recurrence matrices are then integrated to reveal the times when the two systems simultaneously exhibit a recurrence. Considering again the example of two trains, joint recurrence analysis would chart when the trains simultaneously reach a station that each had already visited. Joint recurrence analysis might be particularly useful for assessing synchronization between interacting systems (i.e., systems that can jointly influence one another) (Marwan et al., 2007). A group researcher might, for example, examine the degree to which group members synchronize their activities during face-to-face interactions.

Windowed recurrence analysis is an extension that can be used with any kind of recurrence analysis (e.g., autorecurrence, cross recurrence). In the tutorial above, we calculated recurrence metrics across the entirety of each performance episode for each group. This yielded a single value for each of the recurrence metrics for each group and each episode. Windowed recurrence analysis, however, enables calculating recurrence metrics for subsets of time within each recurrence plot (Webber & Zbilut, 2005). Examining metrics across windows within a recurrence plot sheds light on how the structure of system dynamics changes over time. To illustrate the potential value of windowed analysis using our tutorial dataset, we divided the time series for each group and each performance episode into 10 equal windows, allowing each window to overlap with the next by 20%. Then, we conducted a recurrence analysis on each of the 10 subset windows, calculating recurrence rate, determinism, and entropy. This yielded, for each performance episode, 10 observations of output (i.e., one set of metrics per window of time). Figure 3 depicts the average values from our sample of recurrence metrics across these 10 windows of time within a performance episode. On average, each metric increases over the course of a performance episode, revealing that dynamic structure becomes increasingly predictable and complex. Windowed recurrence analysis could be a powerful tool for group researchers seeking to test hypotheses about how group dynamics change over the course of a time-delimited performance episode. For example, the output of a windowed recurrence analysis could be used with growth models to test whether some groups become more deterministic faster than others over the course of a performance episode.

Implications for Research on Group Dynamics

Recurrence analysis, as this introduction to its conceptual foundations and basic mechanics shows, offers a different analytical mindset for thinking about group dynamics. Growing out of the systems dynamics literature, which for decades has wrestled with the challenges of nonlinear systems, recurrence analysis is a technique unencumbered by the assumptions of traditional analytical techniques in group research, such as the general linear model and growth modeling. As the exemplar application above shows, recurrence analysis is a technique that shares commonalities with the qualitative, descriptive approaches researchers have historically used in longitudinal process-focused group research (e.g., Gersick, 1988, 1989). And yet, by focusing on patterns of recurrent activity, recurrence analysis offers group researchers a novel perspective for testing existing theories using time-series data and developing new theories of group dynamics. Whereas current analytical approaches emphasize the *content* of group activities over time, a recurrence analysis approach emphasizes the *structure* of group activities over time. Considering structure, alongside content, can enrich scholars' understanding of how groups and their members change over time.

For example, a core proposition underlying Gersick's (1988, 1989, 1991) punctuated equilibrium model is that groups undergo phase transitions when faced with a deadline. Further, Gersick's model makes predictions about *when* these transitions are especially likely to occur (e.g., at the temporal midpoint of a time-delimited project) and how the actual timing of transitions might relate to group effectiveness. Although a number of researchers have used quantitative methods to examine transitions in teams (e.g., Knight, 2015; Okhuysen & Waller, 2002; Seers & Woodruff, 1997; Waller,

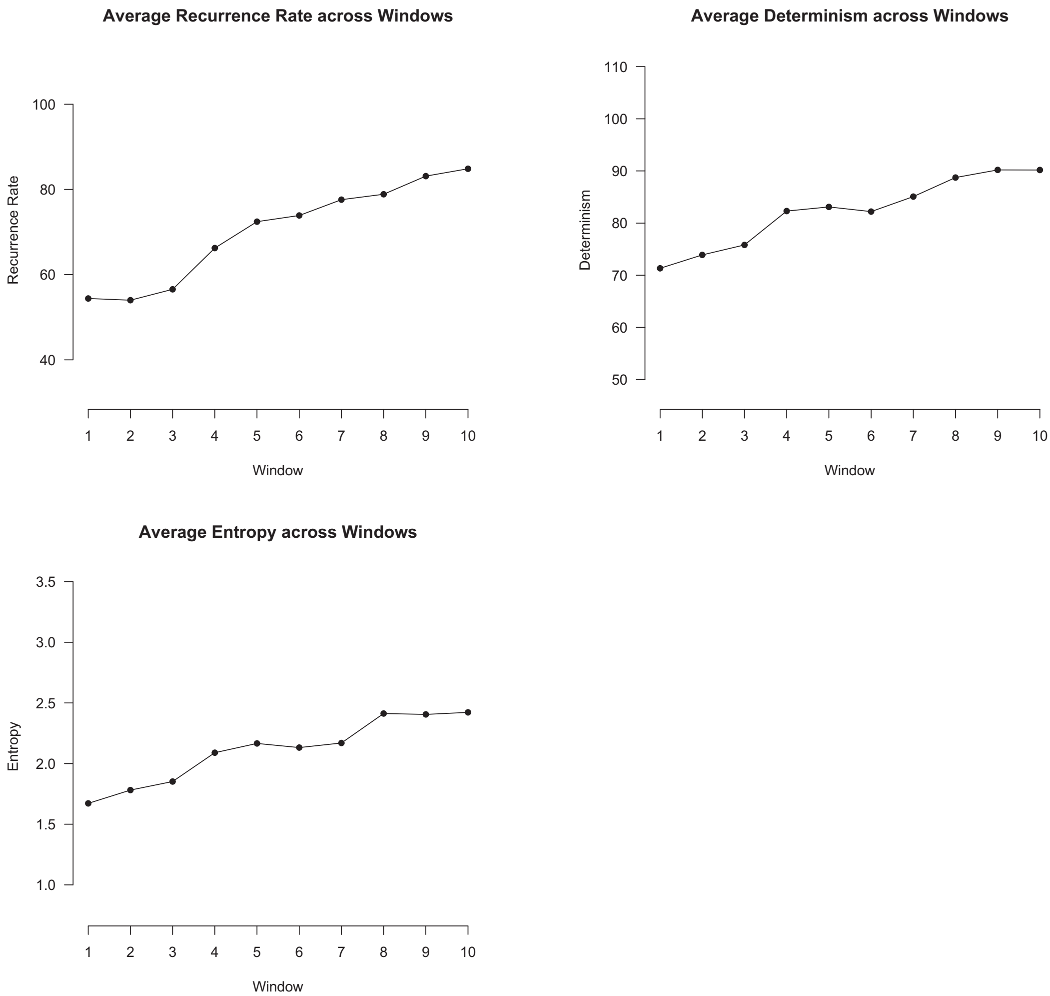

Figure 3. Example of windowed recurrence quantification analysis: average metrics across windows.

Zellmer-Bruhn, & Giambatista, 2002; Woolley, 1998, 2009), analyses of transitions have necessarily been indirect. Because analytical models commonly used in group research presume continuous change over time, they are ill-equipped for detecting truly discontinuous change over time. As such, researchers have made comparisons between different marked phases of activity rather than using nonlinear methods to detect phase shifts. Recurrence analysis offers ways to measure how a group's dynamic structure is changing over time and, thus, could be used to more precisely identify when transitions occur within groups. Using this new approach, researchers could revisit old questions about group task pacing and better understand the timing and implications of phase transitions in groups.

Recurrence analysis is an approach that is also likely to be useful for addressing existing questions about groups and entrainment. The idea that the timing of external events can influence individuals, groups, and organizations is central to an open systems perspective (e.g., Ancona & Chong, 1996; McGrath & Rotchford, 1983). Ancona and Chong (1999) proposed that group dynamics are sensitive to temporal aspects of the overarching environment, such as the pace and rhythm of events, as well as to the cyclical nature of events (e.g., organizational budgetary cycles). Reflecting an open systems perspective, they defined entrainment as "the adjustment of the pace or cycle of an activity to match or synchronize with that of another activity" (Ancona & Chong, 1999, p. 251). Ideas about entrainment have been particularly difficult to test in group research because existing quantitative methods do not easily accommodate assessing synchrony or measuring cyclical dynamics. As described above, however, recurrence analysis provides ways to measure dynamic structure over time. Further, extensions of recurrence analysis, like cross recurrence analysis, offer ways to measure the degree to which two systems are coupled. With cross recurrence analysis, researchers could directly test old and new ideas about the causes and consequences of group entrainment with external environmental pacers.

Related to both phase transitions and entrainment, recurrence analysis may also be useful to researchers studying questions about the emergence of collective phenomena in groups and teams. As a number of scholars have recently underscored, empirical research on the dynamics of emergence—the dynamic interactions among lower-level entities (e.g., individual group member affect) that over time lead to higher-level phenomena (e.g., group affect)—is notably lacking (e.g., Cronin et al., 2011; Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013). One potential reason for this gap is the inability of existing analytical models used in organizational research to reflect the dynamic processes of lower-level units combining and interacting to form collective properties. A number of recent articles have shown that recurrence analysis can be useful for understanding the emergence of coordination in dyads (e.g., Fusaroli & Tylén, 2016; Strang et al., 2014). And our illustration of windowed recurrence analysis (see Figure 3) suggests that the dynamic structure of a group of people working on a collaborative task becomes increasingly predictable and complex over time. One interpretation of this may be that coordination and routines are emerging in these groups to guide group members in interacting with one another. Researchers studying emergence—particularly those using large datasets that track groups in real-time (e.g., Kozlowski et al., 2016)—will likely find tremendous value in using recurrence analysis to assess the dynamic structure of groups.

Beyond addressing existing theory and longstanding research questions, recurrence analysis may stimulate the development of novel theory about group dynamics. A bidirectional relationship exists between the analytical toolsets that researchers possess and the theoretical accounts that researchers can develop about group behavior (Zyphur, 2009). Theoretical frameworks guide the constructs researchers measure, when and how they are measured, and the kinds of relationships posited to exist among them. Methodological and analytical mindsets, however, guide researchers' thinking about what is possible (Zyphur, 2009). Analytical mindsets shape thinking about the very nature of constructs—what can a construct look like? And analytical mindsets shape researchers' thinking about patterns or relationships that may exist among constructs—is a system limited to sequential arrows, or are feedback loops possible? The concepts measured by recurrence analysis—such as how deterministic or complex the structure of group dynamics are—lack clear analogs in existing theory and research on groups. Thinking, however, of groups as more or less structured, and in more or less complex ways, suggests intriguing avenues for research on group dynamics. Why are some groups more predictable in their patterns of activity than others? Why do some groups have more complex patterns of interactions than others? Theory is needed to explore why some groups are more deterministic or more complex than others and how varying dynamic structures might relate to group effectiveness. It may be that different group designs (e.g., pooled interdependence, reciprocal interdependence) provoke different system dynamics. Or, perhaps the task a group must tackle (e.g., creativity task, execution task) shapes its system dynamics. Little is known currently about the roles that determinism and entropy play in the life of a group. Recurrence analysis, and the analytical mindset that it provokes, may stimulate new theoretical directions for conceptual models of group dynamics. Further integration of this technique into the group researcher's toolbox may help break the recurring cycle of commentators lamenting the lack of empirical research on groups as dynamic systems.

References

Ancona, D., & Chong, C. (1996). Entrainment: Pace, cycle, and rhythm in organizational behavior. In B. M. Staw & L. L. Cummings (Eds.), *Research in organizational behavior* (Vol. 18, pp. 251–284). Greenwich, CT: JAI Press.

Ancona, D., & Chong, C. (1999). Cycles and synchrony: The temporal role of context in team behavior. In R. Wageman (Ed.), *Research on managing groups and teams: Groups in context* (Vol. 2, pp. 33–48). Stamford, CT: JAI Press.

Arrow, H., McGrath, J. E., & Berdahl, J. L. (2000). *Small groups as complex systems: Formation, coordination, development, and adaptation*. Thousand Oaks, CA: Sage.

Bales, R. F. (1950). *Interaction process analysis: A method for the study of small groups*. Cambridge, MA: Addison Wesley.

Caraiani, P., & Haven, E. (2013). The role of recurrence plots in characterizing the output-unemployment relationship: An analysis. *PLoS ONE, 8,* e56767. http://dx.doi.org/10.1371/journal.pone.0056767

Coco, M. I., & Dale, R. (2014). Cross-recurrence quantification analysis of categorical and continuous time series: An R package. *Frontiers in Psychology, 5,* 510. http://dx.doi.org/10.3389/fpsyg.2014.00510

Cronin, M. A., Weingart, L. R., & Todorova, G. (2011). Dynamics in groups: Are we there yet? *The Academy of Management Annals, 5,* 571–612. http://dx.doi.org/10.1080/19416520.2011.590297

Dale, R., & Spivey, M. J. (2006). Unraveling the dyad: Using recurrence analysis to explore patterns of syntactic coordination between children and caregivers in conversation. *Language Learning, 56,* 391–430. http://dx.doi.org/10.1111/j.1467-9922.2006.00372.x

Eckmann, J. P., Kamphorst, S. O., & Ruelle, D. (1987). Recurrence plots of dynamical systems. *Europhysics Letters, 4,* 973–977. http://dx.doi.org/10.1209/0295-5075/4/9/004

Edmonds, W. A., Tenenbaum, G., Kamata, A., & Johnson, M. B. (2009). The role of collective efficacy in adventure racing teams. *Small Group Research, 40,* 163–180. http://dx.doi.org/10.1177/1046496408328489

Fusaroli, R., Bjørndahl, J. S., Roepstorff, A., & Tylén, K. (2016). A heart for interaction: Shared physiological dynamics and behavioral coordination in a collective, creative construction task. *Journal of Experimental Psychology: Human Perception and Performance*. Advance online publication. http://dx.doi.org/10.1037/xhp0000207

Fusaroli, R., Konvalinka, I., & Wallot, S. (2014). Analyzing social interactions: The promises and challenges of using cross recurrence quantification analysis. In N. Marwan, M. Riley, A. Guiliani, & C. Webber, Jr. (Eds.), *Translational Recurrences* (pp. 137–155). Cham, Switzerland: Springer International. http://dx.doi.org/10.1007/978-3-319-09531-8_9

Fusaroli, R., & Tylén, K. (2016). Investigating conversational dynamics: Interactive alignment, interpersonal synergy, and collective task performance. *Cognitive Science, 40,* 145–171.

Gelman, A., & Hill, J. (2007). *Data analysis using regression and multilevel/hierarchical models*. New York, NY: Cambridge University Press.

Gersick, C. (1988). Time and transition in work teams: Toward a model of group development. *Academy of Management Journal, 31,* 9–41. http://dx.doi.org/10.2307/256496

Gersick, C. (1989). Marking time: Predictable transitions in task groups. *Academy of Management Journal, 32,* 274–309. http://dx.doi.org/10.2307/256363

Gersick, C. (1991). Revolutionary change theories: A multilevel exploration of the punctuated equilibrium paradigm. *The Academy of Management Review, 16,* 10–36.

Gleick, J. (1997). *Chaos: Making a new science*. New York, NY: Random House.

González, H., Infante, O., Pérez-Grovas, H., Jose, M. V., & Lerma, C. (2013). Nonlinear dynamics of heart rate variability in response to orthostatism and hemodialysis in chronic renal failure patients: Recurrence analysis approach. *Medical Engineering & Physics, 35,* 178–187. http://dx.doi.org/10.1016/j.medengphy.2012.04.013

Gorman, J. C., Cooke, N. J., Amazeen, P. G., & Fouse, S. (2012). Measuring patterns in team interaction sequences using a discrete recurrence approach. *Human Factors, 54,* 503–517. http://dx.doi.org/10.1177/0018720811426140

Hackman, J. R. (1987). The design of work teams. In J. Lorsch (Ed.), *Handbook of organizational behavior* (pp. 315–342). Englewood Cliffs, NJ: Prentice Hall.

Ilgen, D. R., Hollenbeck, J. R., Johnson, M., & Jundt, D. (2005). Teams in organizations: From input-process-output models to IMOI models. *Annual Review of Psychology, 56,* 517–543. http://dx.doi.org/10.1146/annurev.psych.56.091103.070250

Kennedy, D. M., & McComb, S. A. (2014). When teams shift among processes: Insights from simulation and optimization. *Journal of Applied Psychology, 99,* 784–815. http://dx.doi.org/10.1037/a0037339

Knight, A. P. (2015). Mood at the midpoint: Affect and change in exploratory search over time in teams that face a deadline. *Organization Science, 26,* 99–118. http://dx.doi.org/10.1287/orsc.2013.0866

Kozlowski, S. W. J., Chao, G. T., Chang, C.-H., & Fernandez, R. (2016). Team dynamics: Using "big data" to advance the science of team effectiveness. In S. Tonidandel, E. King, & J. Cortina (Eds.), *Big data at work: The data science revolution and organizational psychology* (pp. 272–309). New York, NY: Routledge Academic.

Kozlowski, S. W. J., Chao, G. T., Grand, J. A., Braun, M. T., & Kuljanin, G. (2013). Advancing multilevel research design: Capturing the dynamics of emergence. *Organizational Research Methods, 16,* 581–615. http://dx.doi.org/10.1177/1094428113493119

Kozlowski, S. W. J., Gully, S. M., Nason, E. R., & Smith, E. M. (1999). Developing adaptive teams: A theory of compilation and performance across levels and time. In D. R. Ilgen & E. D. Pulakos (Eds.), *The changing nature of work performance: Implications for staffing, personnel actions, and development* (pp. 240–292). San Francisco, CA: Jossey-Bass.

Kozlowski, S. W. J., & Ilgen, D. R. (2006). Enhancing the effectiveness of work groups and teams. *Psychological Science in the Public Interest, 7,* 77–124.

Marks, M. A., Mathieu, J. E., & Zaccaro, S. J. (2001). A temporally based framework and taxonomy of team processes. *Academy of Management Review, 26,* 356–376.

Marwan, N. (2008). A historical review of recurrence plots. *The European Physical Journal Special Topics, 164,* 3–12. http://dx.doi.org/10.1140/epjst/e2008-00829-1

Marwan, N. (2011). How to avoid potential pitfalls in recurrence plot based data analysis. *International Journal of Bifurcation and Chaos in Applied Sciences and Engineering, 21,* 1003–1017. http://dx.doi.org/10.1142/S0218127411029008

Marwan, N., Carmen Romano, M., Thiel, M., & Kurths, J. (2007). Recurrence plots for the analysis of complex systems. *Physics Reports, 438,* 237–329. http://dx.doi.org/10.1016/j.physrep.2006.11.001

Mathieu, J., Maynard, M. T., Rapp, T., & Gilson, L. (2008). Team effectiveness 1997–2007: A review of recent advancements and a glimpse into the future. *Journal of Management, 34,* 410–476. http://dx.doi.org/10.1177/0149206308316061

Mathieu, J. E., & Rapp, T. L. (2009). Laying the foundation for successful team performance trajectories: The roles of team charters and performance strategies. *Journal of Applied Psychology, 94,* 90–103. http://dx.doi.org/10.1037/a0013257

McGrath, J. E. (1986). Studying groups at work: Ten critical needs for theory and practice. In P. S. Goodman (Ed.), *Designing effective work groups* (pp. 362–392). San Francisco, CA: Jossey-Bass.

McGrath, J. E. (1991). Time, interaction, and performance (TIP): A theory of groups. *Small Group Research, 22,* 147–174. http://dx.doi.org/10.1177/1046496491222001

McGrath, J. E., & Rotchford, N. L. (1983). Time and behavior in organizations. In L. L. Cummings & B. M. Staw (Eds.), *Research in organizational behavior* (Vol. 5, pp. 57–101). Greenwich, CT: JAI Press.

Okhuysen, G. A., & Waller, M. J. (2002). Focusing on midpoint transitions: An analysis of boundary conditions. *Academy of Management Journal, 45,* 1056–1065. http://dx.doi.org/10.2307/3069330

Richardson, D. C., & Dale, R. (2005). Looking to understand: The coupling between speakers' and listeners' eye movements and its relationship to discourse comprehension. *Cognitive Science, 29,* 1045–1060. http://dx.doi.org/10.1207/s15516709cog0000_29

Seers, A., & Woodruff, S. (1997). Temporal pacing in task forces: Group development or deadline pressure. *Journal of Management, 23,* 169–187. http://dx.doi.org/10.1177/014920639702300204

Shockley, K., Santana, M. V., & Fowler, C. A. (2003). Mutual interpersonal postural constraints are involved in cooperative conversation. *Journal of Experimental Psychology: Human Perception and Performance, 29,* 326–332. http://dx.doi.org/10.1037/0096-1523.29.2.326

Strang, A. J., Funke, G. J., Russell, S. M., Dukes, A. W., & Middendorf, M. S. (2014). Physio-behavioral coupling in a cooperative team task: Contributors and relations. *Journal of Experimental Psychology: Human Perception and Performance, 40,* 145–158. http://dx.doi.org/10.1037/a0033125

Takens, F. (1981). Detecting strange attractors in turbulence. In D. Rand & L. S. Young (Eds.), *Lecture notes in mathematics: Vol. 898. Dynamical systems and turbulence, Warwick 1980* (pp. 366–381). Berlin, Germany: Springer-Verlag. http://dx.doi.org/10.1007/BFb0091924

Tasca, G. A., & Lampard, A. M. (2012). Reciprocal influence of alliance to the group and outcome in day treatment for eating disorders. *Journal of Counseling Psychology, 59,* 507–517. http://dx.doi.org/10.1037/a0029947

Totterdell, P., Kellett, S., Teuchmann, K., & Briner, R. B. (1998). Evidence of mood linkage in work groups. *Journal of Personality and Social Psychology, 74,* 1504–1515. http://dx.doi.org/10.1037/0022-3514.74.6.1504

Tuckman, B. W. (1965). Developmental sequence in small groups. *Psychological Bulletin, 63,* 384–399. http://dx.doi.org/10.1037/h0022100

Waller, M. J., Zellmer-Bruhn, M. E., & Giambatista, R. C. (2002). Watching the clock: Group pacing behavior under dynamic deadlines. *Academy of*

Management Journal, 45, 1046–1055. http://dx.doi.org/10.2307/3069329

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications in the social science*. New York, NY: Cambridge University Press. http://dx.doi.org/10.1017/CBO9780511815478

Webber, C. L., Jr., & Zbilut, J. P. (1994). Dynamical assessment of physiological systems and states using recurrence plot strategies. *Journal of Applied Physiology, 76,* 965–973.

Webber, C. L., & Zbilut, J. P. (2005). Recurrence quantification analysis of nonlinear dynamical systems. In M. A. Riley & G. C. Van Orden (Eds.), *Tutorials in contemporary nonlinear methods for the behavioral sciences* (pp. 26–94). Arlington, VA: National Science Foundation.

Woolley, A. W. (1998). Effects of intervention content and timing on group task performance. *Journal of Applied Behavioral Science, 34,* 30–46. http://dx.doi.org/10.1177/0021886398341002

Woolley, A. W. (2009). Means vs. ends: Implications of process and outcome focus for team adaptation and performance. *Organization Science, 20,* 500–515. http://dx.doi.org/10.1287/orsc.1080.0382

Zyphur, M. J. (2009). When mindsets collide: Switching analytical mindsets to advance organization science. *The Academy of Management Review, 34,* 677–688. http://dx.doi.org/10.5465/AMR.2009.44885862

Received September 14, 2015
Revision received March 10, 2016
Accepted March 15, 2016 ■