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Development of a Synchronization Coefficient for Biosocial Interactions in Groups and Teams

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Abstract

Body movements, autonomic arousal, and electroencephalograms (EEGs) of group members are often coordinated or *synchronized* with those of other group members. Linear and nonlinear measures of synchronization have been developed for pairs of individuals, but little work has been done on measures of synchronization for groups. We define a new synchronization coefficient, S_E, for a group based on pairwise correlations in time series data and employing the notions of a group *driver*, who most drives the group's responses, and *empath*, who is most driven by the group. S_E is developed here in the context of emotional synchronization based on galvanic skin response time series. A simulation study explores its properties, the balance between strong versus weak autocorrelational effects, transfer, group size, and direct versus oscillatory functions. Distributions of S_E are not affected by group size up to 16 members. Norms for interpreting the coefficient are presented along with directions for new research.

Keywords

group process, interactive analysis, modeling, simulations, work groups

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Emotions in groups can be contagious. When everyone's positive and negative emotional tides follow closely together in time, they are said to be synchronized. Synchronization resembles some forms of coordination, such as neuromuscular coordination, where there is a relatively exact or proportional tracking of body sway, hand and head movements, autonomic arousal, or electroencephalogram (EEG) readings between two or more people. There is a theory building effort currently underway to uncover connections between synchronization in arousal, cognition, task structures, and performance outcomes in dyads and teams (Gipson, Gorman, & Hessler, 2016; Guastello et al., 2016; Salas et al., 2015). Outcomes of interest include better therapy sessions when the therapist and client are synchronized with regard to autonomic arousal (Marci, Ham, Moran, & Orr, 2007; Orsucci et al., 2016), body movements (Ramseyer & Tschacher, 2011, 2016), or speech patterns (Reuzel et al., 2014). Better work performance outcomes would also be expected when teams are similarly synchronized (Elkins et al., 2009; Henning, Boucsein, & Gil, 2001; Stevens & Galloway, 2016).

Studies of synchronization proceed from a broader awareness that group processes need to be studied as events over time (Arrow, Poole, Henry, Wheelan, & Moreland, 2004). Some perspectives go several steps further by using specific principles from nonlinear dynamical systems (NDS) theory such as attractors, bifurcations, chaos, fractals, entropy, catastrophes, phase shifts, self-organization, and emergence to explain the patterns in the temporal events (Arrow, 2005; Guastello, 2009; Wheelan & Williams, 2003). Due to length considerations, some familiarity with basic concepts from NDS (limit cycle attractors, oscillator dynamics, chaos, self-organization, etc.) is assumed in what follows. There is an extensive body of literature available; for further background details see, for example, Kaplan and Glass (1995), Sprott (2003), and Guastello and Liebovitch (2009), in addition to other works cited in this article.

Although several computational methods have been offered for quantifying the level of synchronization between two people, little has been done to develop a metric that captures the overall amount of synchronization in a group as a whole. Such a metric would facilitate research that compares levels of group synchronization with interesting verbal, behavioral, and situational variables of interest. It would also facilitate investigations into emergent group-level phenomena that cannot be reduced to the contributions of individuals or dyads. Thus, the primary objective of the present study was to develop such a metric.

Our approach for the group synchronization metric is to build it up from pairwise (dyadic) measures of influence between each pair of members in a group. A virtue of this approach is its generality: It can be applied to linear dyadic measurements or more sophisticated nonlinear dyadic measurements and can, therefore, facilitate important ongoing assessments when various nonlinear models are more appropriate. Once the full set of pairwise measurements of influence (pairwise synchronization coefficients built up from time series analysis in our case here) has been determined (according to a linear or nonlinear model), theses coefficients are organized as a matrix of pairwise synchronization coefficients (e.g., person 1 on person 2, person 1 on person 3, person 2 on person 1, person 3 on person 1, and so on). Thus, the matrix of pairwise synchronization coefficients can written as $[P_{i,j}]$, where $P_{i,j}$ is the *i*th person's influence on the *j*th person, as described in a subsequent section of this article.

The next step involves identifying (a) the member *most influenced* by the other members of the group—the *empath*—who is the person with the largest sum of pairwise synchronization coefficients of others on him or her and (b) the member *with the most influence* on the other members of the group—the *driver*—who is the person with the largest sum of pairwise synchronization coefficients of him or her on others.

Finally, one sets up a problem much like an ordinary multiple linear regression. The values of the empath's pairwise synchronization coefficients (others influence on the empath) are regressed as the dependent variables on the values of the other members' influence on everyone else. This regression of how well the empath's degree of being influenced by the others is then used to extract a metric that is analogous to the coefficient of determination (R^2), which is a measure of the global fit, and is taken to be the degree of group synchronization (S_E).

In the following sections, we begin by presenting the details of the central features of synchronization, and then discuss the details of the statistical analyses that are used most often for dyadic analyses, and some findings of particular interest to emotional synchronization phenomena. Then, we develop in detail a new synchronization coefficient for groups and present a simulation study that explores its properties. We conclude with a discussion of the results, including some practical issues with utilizing the technique and a suggested research agenda.

Principles of Synchronization

The dynamics of synchronization involve self-organization and emergence constructs and bear some similarity to Haken's (1984) notion of driver–slave relationships. Unlike the driver–slave relationship, which is unidirectional, synchronization phenomena are bi-directional or *N*-directional in the case of groups. A prototype illustration is the synchronization of a particular species of fireflies from Southeast Asia (Strogatz, 2003). The flies flash on and off, which is their means of communicating with each other. In the early part of the evening, each one flashes at its own rate. As they interact, they pulse on and off in greater synchrony, so that by the end of the evening, the whole forest lights up and turns off as if one were flipping a light switch. The common features among the many examples are that synchronized systems contain two oscillators, a feedback loop between them, and a control parameter that speeds up the oscillation. When the speed reaches a critical level, *phase lock* sets in and the synchronized pulsing can be observed.

The prototype synchronization dynamics are not always simple and direct. The "oscillators" could be complex self-organized events. Galvanic skin response (GSR) time series and EEG, for instance, result from the combined activity of multiple neural circuits that are *supposed* to act chaotically over time, even though they might result in oscillating behavioral outcomes. From the between-person perspective, three coupled oscillators are sufficient to produce chaos (Newhouse, Ruelle, & Takens, 1978). Not all possible combinations of oscillators and parameters will do so (Pikovsky, Rosenblum, & Kurths, 2001; Puu, 1993); they could flatten each other out, however, and some oscillators can become unstable in the presence of others (Puu, 2000). Thus, the assumption that the synchronizing time series are pure oscillators is not universally applicable.

The level of synchronization could be matters of degree and direction. Feedback could be a one-way or an imbalanced two-way relationship. The feedback could be positive–positive, in which the participants feed off each other and their emotions go up and down at the same time. Feedback could also be positive–negative, such that one person tends to excite the second, but the second dampens the first to maintain focus or calm. There is also the possibility of negative–negative synchronization, which might have the appearance of two people on an emotional see-saw (Guastello, 2016).

The task also imposes different requirements for coordination and synchronization. Dyads could be (a) taking turns in conversation, (b) taking different but synchronized compatible actions, or (c) working in parallel on a task where they can have different levels of interaction. Figure 1 contains a pair of GSR records for two people working on a vigilance task that required participants to look for an intruder in a virtual reality security camera display showing scenes from an empty building, while performing a second task (Guastello, 2016). The person represented in the upper chart was positively influenced by the person in the lower chart, meaning that arousal levels in the upper chart tended to go up and down within a few seconds of the movement from the person in the lower chart. The person in the lower chart, however, was negatively affected by the person in the upper chart, meaning that upward and downward fluctuations from the upper chart tended to be dampened by the person in the lower chart once they were experienced.

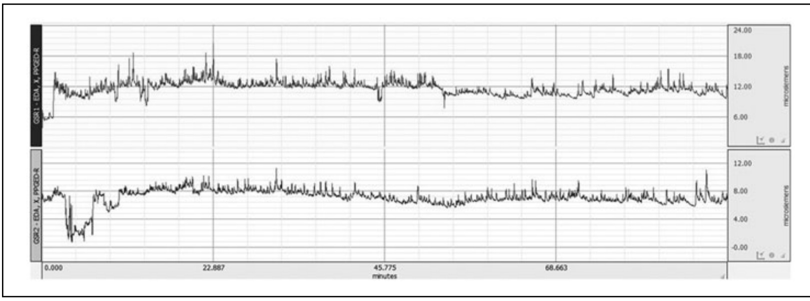

Figure 1. GSR time series for a dyad performing a vigilance dual task.
Source. Reprinted from Guastello (2016, p. 66). Copyright 2016 by the Society for Chaos Theory in Psychology & Life Sciences.
Note. GSR = galvanic skin response.

Teams of three or more people could be (a) synchronized with each other in any of the modes possible for dyads, (b) focused on an external situation that is changing, or (c) both, as depicted in the diagram in Figure 2. The linkage diagram in Figure 2 represents the task configuration for a team of four people working in an emergency response (ER) simulation against a single opponent (also human, not a computer-generated avatar). The activity contained a defined turn-taking process. Figure 3 is a set of GSRs generated from one such simulation (Guastello et al., 2016). The upper panel of time series contains raw observations generated at 120 samples per second; the opponent's data are designated as GSR5. The lower panel of time series contains the same raw data as the upper panel except that the observations were down-sampled to one observation per second. The appearance of synchronization was still present but less pronounced.

Dyadic Models of Synchronization

In this section, we make use of standard time series analysis techniques (see Ozaki, 2012). It is assumed that the analyses of the discussed physiological metrics are performed on continuously streaming data, rather than discrete event-based data, to capture the nonlinear dynamics in the process. Although event markers could be incorporated into the experimental design as additional elements to create discrete event-based data, the use of such event marking is not required for basic modeling with the computations described next.

There are a few boundary conditions that need to be observed when choosing a statistical model. The general model for all candidate models is shown below.

$$X_2 = f\left(X_1, P_1\right). \tag{1}$$

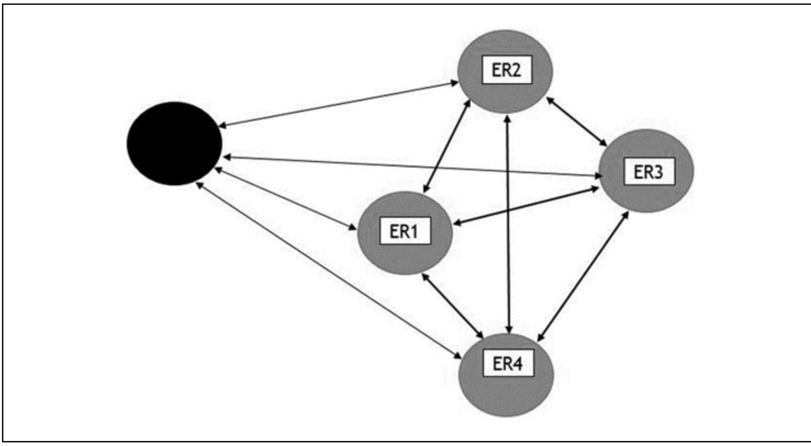

Figure 2. Four members of an emergency response (ER) team coordinate responses and synchronize arousal levels as they work against a situation that is changing over time.

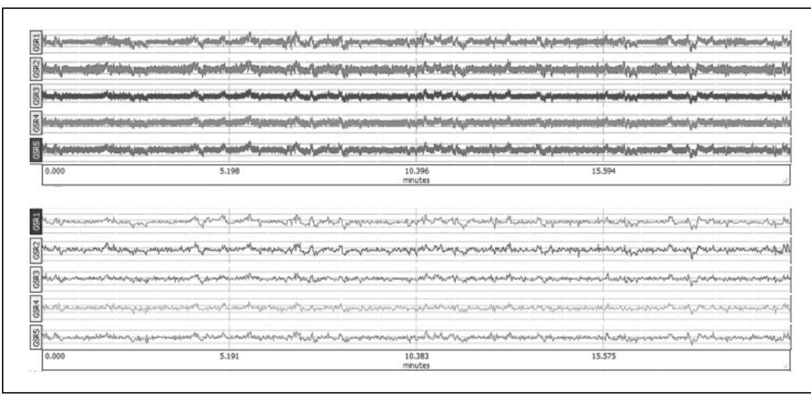

Figure 3. GSR readings for five people playing the emergency response board game with a defined turn-taking sequence.
Source. Reprinted from Guastello et al. (2016, p. 231), Copyright 2016 by the Society for Chaos Theory in Psychology & Life Sciences.
Note. Upper panel: Raw data in millivolts. Lower panel: Data resampled at one observation per second. GSR = galvanic skin response.

Here $X = \{X_1, X_2, \ldots\}$ is the time series for the target person, and $P = \{P_1, P_2, \ldots\}$ is the other person. The statistical model needs to determine *Granger causality*; that is, P must explain X over and above the autocorrelation X (with itself). This is an important constraint to guard against spontaneous synchronization. Two entities can behave similarly over time for reasons that are completely independent of one another. One also wants point estimation and a measure of the size of synchronization effect, not simply a significance test.

Several types of nonlinear analyses have been used to assess the synchronization between pairs of people, such as recursion quantification analysis (Delaherche et al., 2012; Orsucci et al., 2016; Reuzel et al., 2014), phases of oscillators (Delaherche et al., 2012; Gorman, Amazeen, & Cooke, 2010; Richardson, Garcia, Frank, Gergor, & Marsh, 2012), statistical models that are based on the assumption of pure oscillators (Butner, Amazeen, & Mulvey, 2005; Butner & Story, 2011), chaos (Guastello, 2016; Guastello et al., 2016; Guastello, Pincus, & Gunderson, 2006), wavelet analysis (Likens, Amazeen, Stevens, Galloway, & Gorman, 2014), and symbolic dynamics (Stevens & Galloway, 2016; Stevens, Galloway, & Lamb, 2014; Stevens, Gorman, Amazeen, Likens, & Galloway, 2013). Given the range of available options, we selected the exponential structure as a reference model because it can determine whether the time series is chaotic, self-organizing (1/*f*), oscillating, dampening, or moving toward a fixed point—providing a wide range of possible dynamics all in one analysis. Self-organized systems tend to produce time series of behavior that have fractal dimensions between 1.0 and 2.0 (Bak, 1996; Guastello & Gregson, 2011). Calmer systems would fall closer to 1.0 and thus be well approximated by a linear time series analysis. The linear model also serves as a helpful reference model because it is a common choice, and it also provides the necessary elements for the new synchronization coefficient. More volatile systems would produce time series with higher dimensions, and thus be represented better by an appropriate nonlinear model.

The simplest structure in the exponential model series (Guastello & Gregson, 2011; Guastello, Nathan, & Johnson, 2009) is autocorrelational, and calculated through nonlinear regression, as shown with the following equation.

$$z_2 = \theta_1 \exp\left(\theta_2 z_1\right) + \theta_3. \tag{2}$$

In Equation 2, θ_2 is the Lyapunov exponent. z is the time series variable X that was transformed by location and scale.[1] When testing a model, θ_1 or θ_3 can be dropped to preserve the statistical significance of θ_2. Statistical models that are calculated with a least-squares procedure are usually compared on the basis of R^2, percentage of variance accounted for. The calculation of the synchronization coefficient requires the use of R (unsquared).

Equation 2 can be used as a test for chaos by examining the signs of θ_2 and θ_3. Not all expanding functions are chaotic; chaotic processes contain both expanding and contracting trajectories. Thus, if the exponent is positive and the constant, θ_3, is negative, one has signs of a chaotic process. The Lyapunov dimension, D_L, is equal to $\exp(\theta_2 t)$; $t = 1$ if all time intervals are equal, as they are in this application. However, previous work with GSR data (Guastello, 2016; Guastello et al., 2016) showed that θ_3 should be dropped.

The second model from the series that was adopted here is an expansion of Equation 2 in which a second exponential function in Equation 2 replaces the constant.

$$z_2 = \theta_1 \exp(\theta_2 z_1) + \theta_3 \exp(\theta_4 z_1) + \theta_5. \tag{3}$$

This structure has been used to assess synchronization or transfer effects from a conversation partner to the target person (Guastello et al., 2006), GSR series from dyads working on a vigilance task (Guastello, 2016), and teams playing an ER board game (Guastello et al., 2016). The data analyses showed that two of the regression weights were not necessary, and the model simplified to create Equation 4.

$$z_2 = \theta_1 \exp(\theta_2 z_1) + \exp(\theta_4 P_1). \tag{4}$$

In Equation 4, P is the partner to the target person z, and this GSR series was also transformed by location and scale. The same simplification was needed in previous studies of dyads (Guastello, 2016; Guastello et al., 2006; Guastello et al., 2016).[2] The regression weight, θ_4, is the *transfer* coefficient that is used in the calculation of the synchronization coefficient. It represents the impact of a second person on the target person beyond the simple autocorrelation. Thus, it captures the amount of synchronization between P and z.

Linear models would have a similar but simpler structure. The autocorrelation function would be as follows.

$$X_n = \beta_0 + \beta_1 X_{n-j}, \tag{5}$$

where X is the GSR series for a target person and $j > 0$ is the lag. An autocorrelation is a linear relationship so long as the autocorrelation is positive. Negative autocorrelations indicate an oscillation; an upward movement is followed by a downward movement.

Equation 5 can accommodate synchronicity by adding the response from the second person with a second regression weight (β_2).

$$X_n = \beta_0 + \beta_1 X_{n-j} + \beta_2 P_{n-j}. \tag{6}$$

Then, the amount of synchronization between P and X is represented by the transfer function β_2 and where $j > 0$ is the lag.[3]

The use of any time series model requires that one determine an optimal lag length. Lag length reflects time required for X_{n-j} to produce X_n. Several methods for determining lag length are available, but the results do not always agree (Guastello et al., 2016; Guastello, Reiter, & Malon, 2015). For practical purposes of analysis, one typically commits to one of the standard methods. The issue of choosing a lag length is revisited later in this article.

Group Synchronization Coefficient

Prior Approaches

Prior efforts to develop a synchronization coefficient for groups and teams have been predicated on the data sources that the researchers wanted to synchronize and the underlying assumptions about their dynamics. The phase clustering concept originated with the expectation that the observable behavior was an oscillating function such as finger tapping, rocking in a rocking chair, or the flashing of fireflies (Pikovsky et al., 2001; Richardson et al., 2012). The actions of any two people would be synchronized to the extent that their phase differences in movement were minimal. Figure 4 shows two perfect oscillators that are slightly out of phase even though they are completing their cycles at the same frequency over time. The calculation of group synchronization would involve taking a function of the phase of each time series, finding the average of that function across people, then making one more calculation to arrive at the metric. The phase cluster metric has been shown to differentiate experimental conditions that manipulated the likelihood of synchronization in a rocking chair task (Richardson et al., 2012). Richardson et al. (2012) also remarked, however, that the phase cluster metric did not reflect leader–follower relationships among the individuals, which could affect the level of synchronization of the group as a whole.

A related idea translated the set of biometric time series into a distance coefficient. Elkins et al. (2009) examined synchronization in heart rate variability among team members engaged in a computer simulation where an ER team was cleaning a building of armed combatants. Some of the pairwise indicators they assessed were phase differences between dynamics such as the prototype in Figure 4. Their team-level metric was based on distance across N dimensions (team members). The differences in heart rate variability occurring over a fixed amount of time were calculated, squared, and summed over team members; the synchronization metric was the square root of the sum. The metric was successful in distinguishing high- and low-performing teams. The metric did not appear to distinguish autocorrelation effects from the specific impact of one person on another in any sequential analysis.

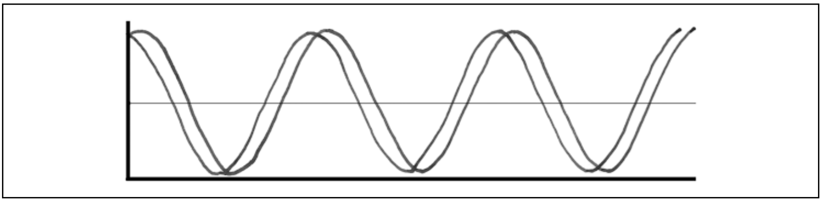

Figure 4. Two oscillators that are slightly out of phase.

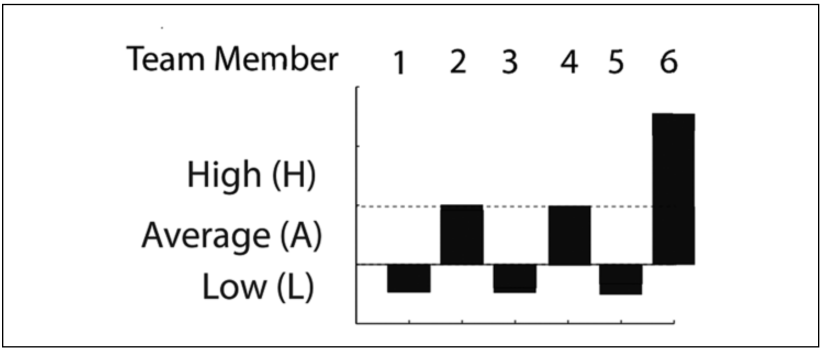

Figure 5. Example of a synchronization symbol.
Source. Reprinted from Stevens and Galloway (2016, p. 275), Copyright 2016 by the Society for Chaos Theory in Psychology & Life Sciences.

The symbolic dynamics approach (Stevens & Galloway, 2016; Stevens et al., 2014; Stevens et al., 2013) was, strictly speaking, not a measurement of group synchronization. Rather, it looked for patterns of EEG activation across six team members, some of which could reflect synchronization, and how often those patterns changed. The patterns could be represented by one of 25 symbols, an example of which appears in Figure 5. The symbols are calculated at very short time intervals and are expected to change over time. The volatility of change (in symbol codes) over the data collection period is calculated as a Shannon entropy coefficient. Self-organized and synchronized sequences would exhibit lower entropy values. Relative to occupational performance criteria, entropy was lower in high-performing groups in the submarine navigation simulation during epochs in which the team was focusing attention on the central commander, and lower among high-performing groups during epochs that demanded individualized action. Pairwise comparisons among team members' sequences of EEG arousal codes can be evaluated with a mutual entropy coefficient, which is a variant of Shannon entropy that is interpreted like a correlation.

The Shannon (1948) entropy metric was first introduced to assess the quality of long-distance telephone communication and quickly became the basis of a general theory of communication (Shannon & Weaver, 1949). It has had extensive use in the analysis communication and choice sequences (Attneave, 1959; Dabbs & Ruback, 1987; Griessmair, Strunk, Vetschera, & Koeszegi, 2011). One of its limitations, however, is that it does not take the serial dependency between system states into account in the calculation of entropy; a frequency distribution of categorical states that is executed in two or more different temporal orders would produce the same measurement of entropy. There are other measures of entropy that do take sequence into account, however (Guastello & Gregson, 2011), and importantly converge to a Lyapunov exponent under limiting conditions.

New Coefficient

The new synchronization coefficient builds on the statistical analysis of dyadic relationships. Within a team of four people, there would be 12 two-way dyadic linkages or transfer effects (N people × $N - 1$). Although there is no a priori reason to expect particular linkages to be tight, loose, positive, or negative, one could devise studies that search for variables that are connected to different linkage properties. Based on the differences among dyads that have been observed in other types of tasks, however, it is possible to anticipate that some team members would be more influential than others on their teammates, and some team members would be more responsive than others to their teammates. Thus, we define two new constructs for studying synchronization in team: the *drivers* and the *empaths*. Drivers would be the individuals who have the strongest physiological effect on others in the group (i.e., other players were more likely to synchronize to their physiological behaviors). Empaths would be the individuals who are most responsive to other members in the group (i.e., they were more likely to synchronize to others' physiological trends).

The designations of drivers and empaths would be determined statistically as explained below in conjunction with Table 1. For any pair of people, the linear models in Equations 2 and 4 or the nonlinear models in Equations 5 and 6 can be calculated with one person's GSR data as the target time series (z_1 or X_n) and the partner's data as a potentially synchronized series (P_{n-j}). The two series can be analyzed in the other direction so that the partner becomes the target and the previous target becomes the partner. The synchronization coefficients would be θ_4 in Equation 4 and β_2 in Equation 6.

For larger groups, however, there are many potential autocorrelation and transfer effects, and most of the transfer effects are probably not symmetrical. For instance, Gottman (1979) and Levinson and Gottman (1983) found in

Table 1. Prototype Matrix of Synchronization Coefficients for a Group With Four Members.

		To				
		P_1	P_2	P_3	$\cdots P_n$	Driver score
From	P_1	$\mathbf{AR_1}$	R_{12}	R_{13}	R_{1n}	$\Sigma R^2{}_1$
	P_2	R_{21}	$\mathbf{AR_2}$	R_{23}	R_{2n}	$\Sigma R^2{}_2$
	P_3	R_{31}	R_{32}	$\mathbf{AR_3}$	R_{3n}	$\Sigma R^2{}_3$
	P_n	R_{n1}	R_{n2}	R_{n3}	$\mathbf{AR}_n$	$\Sigma R^2{}_n$
Empath score		$\Sigma R^2{}_1$	$\Sigma R^2{}_2$	$\Sigma R^2{}_3$	$\Sigma R^2{}_n$	

their studies of distressed married couples that the influence of one partner on the other was more often asymmetric in the couples who were more likely to break apart than the couples who remain together after therapy. In other words, one could predict the arousal level for one spouse during a conflict period from the arousal level of the other, but not necessarily the other way around. Importantly, high degrees of reactivity or synchronization were also predictive of dissolution if the content of the verbal exchange was negative. Guastello et al. (2006) found evidence of non-symmetric influence to varying degrees when two people who met each other for the first time engaged in conversation, although the presence of any level of influence was more readily detected through a nonlinear analysis of GSR levels than through a linear analysis. Gottman (1979) interpreted the presence of a one-way influence effect as a dominance relationship. A later study that involved two people working together on a laboratory task showed similar asymmetries, but also other types of asymmetries, such that one person could have an arousing effect on the partner, while the partner could have a dampening effect on the other (Guastello, 2016).

Thus, we introduce the following matrix argument to simplify the determination of the person who has the most influence on the rest of the group and the person who is most responsive to the other group members. Table 1 is a prototype matrix **P** of synchronization coefficients. The diagonal values are autocorrelations. The off-diagonal entries are synchronization coefficients. The off-diagonal elements are organized so that they represent the influence of the person in the row index on the person in the column index. The matrix can be filled with coefficients from either a linear or nonlinear analysis.

The sum of squared coefficients in the rows can be compared so that the person with the largest value is the *driver* of others' responses. The sum of squared coefficients in the columns can be compared so that the person with the largest value is the *empath*. The computations on the rows and columns were borrowed from factor analysis where the initial values of communality and eigenvalues are established. Psychologically, the computation on the rows implies that the drivers are driving themselves as well as driving other people. Each person in the group is finding a balance between driving or influencing others and being influenced by them.

The empath would be most receptive and less driving than the driver in most cases, but not necessarily the least driving of the group. Empathy is usually defined as having a cognitive and an emotional component. The cognitive component is the ability of one person to see another person's point of view, even though it may be different from their own. The emotional component is the ability to experience vicariously the emotions of other people. The latest thinking on the empathy trait is that it might contain other facets such as *self-regulation* of emotion (Gerdes, Leitz, & Segal, 2011; Lietz et al., 2011), which makes the construct more similar to emotional intelligence. Correlations between .55 and .62 between emotional intelligence and empathy as defined by Gerdes et al. (2011) have been reported (Guastello et al., 2016).

Responsiveness does not necessarily mean following the same direction of increasing or decreasing arousal. Empathetic people can also detect arousal levels and calm the others down (Guastello, 2016). There are also situations in which empathy in the sense of accurate detection of the partner's emotional state does not produce any response at all (Winczewski, Bowen, & Collins, 2016).

Table 2 is a set of values of synchronization coefficients that were computed from actual GSR time series for a group of four people participating in an ER simulation using the linear set of coefficients. In the example, Person 1 would be the driver of the group, and Person 2 would be the empath.

The calculation of the team-wide measure of group synchronization, S_E, is based on the logic inherent in multiple regression. It involves some of the matrix calculations that are present, but generally not seen, in standard multiple regression as performed by commonly used software; see, for example, Tabachnick and Fidell (2007, Appendix A) for background. The first step is to identify the empath, which is P_2 in the example. Second, the column of coefficients for P_2 is removed, the autocorrelation entry AR_2 is dropped, and the remaining coefficients become a column vector $\mathbf{V'}$.

Third, P_2's row is also removed, leaving a square matrix $\mathbf{M}$. Thus, if the original group consisted of four people and the empath is removed, $\mathbf{M}$ is a 3×3 matrix (and always square).

Fourth, take the inverse of $\mathbf{M}$ and calculate a vector of weights:

$$\mathbf{Q} = \mathbf{M}^{-1}\mathbf{V}'. \tag{7}$$

Table 2. Sample Matrix of Coefficients Representing Autocorrelations, Drivers, and Empaths.

	To person				
	1	2	3	4	Driver score
From Person 1	.6040	.4050	.2260	.2310	.6333
From Person 2	.1090	.5480	.1930	.1830	.3829
From Person 3	.0620	.1390	.3590	.1670	.1799
From Person 4	.0330	.0710	.0980	.2920	.1010
Empath score	.3816	.4887	.2268	.2000	

The elements (weights) of **Q** are comparable in meaning to regression weights where the empath is a (human) dependent measure, and the other members of the group are independent variables. The fifth and final step is

$$S_E = \mathbf{V}'\mathbf{Q}. \tag{8}$$

In the example, reduced vector **V’** is

0.4050
0.1390
0.0710

The reduced matrix **M** is

0.6040	0.2260	0.2310
0.0620	0.3590	0.1670
0.0330	0.0980	0.2920

The vector of weights **Q** is

0.5399
0.2479
0.0989

The synchronization coefficient S_E is 0.2602.

Even though the logic of the computation follows that of multiple linear regression, neither matrix **P** nor **M** contains 1.0 in the diagonal entries, and neither is symmetric as would be the case with a standard correlation matrix. Thus, it is not guaranteed that the range of values for S_E would be confined between 0 and 1. Thus, the following simulation studies were conducted to determine the range of S_E under different plausible conditions by varying diagonal values, off-diagonal values, and matrix size.

Simulations

Simulation 1: Diagonals and Off-Diagonal Ranges

The goal of this analysis was to assess the impact of the ranges of values appearing on the diagonal and off-diagonal matrix entries on the size of the synchronization coefficient. This analysis examined combinations of diagonal values within three constrained ranges, which were realistic in light of our lab work in progress with GSR data, and different proportions of negative values in the starting matrix. Negative values of synchronization in the off-diagonal can be interpreted as inhibition effects between a pair of participants. All values of S_E were calculated for hypothetical groups of four. There were three diagonal conditions (Factor A) and four off-diagonal conditions (Factor B):

A1: Diagonals were randomly generated values between .90 and .99.
A2: Diagonals were randomly generated values between .50 and .59.
A3: Diagonals were randomly generated values between .20 and .29.
B1: Off-diagonals were all positive, ranging from $0 < r_{ij} < 1$.
B2: Off-diagonals were 1/3 negative, ranging from $-.5 < r_{ij} < 1$.
B3: Off-diagonals were ½ negative, ranging from $-1.0 < r_{ij} < 1$.
B4: Off-diagonals were 2/3 negative, ranging from $-1.0 < r_{ij} < .5$.

The experimental design was fully crossed, and there were 10 replications for each combination of conditions. The dependent measure was the S_E generated from the pairs of conditions. When generating the samples, one cell, A3-B2, contained an outlier value of $S_E > 100.00$. It was replaced with a new sample of 10. The replacement sample did not contain such an outlier.

Levene's test of homogeneity of variance among the 12 cells was significant at $p < .10$, $F(11, 108) = 1.784$, $p = .065$. Thus, any differences in means could be confounded with differences in variance. Neither of the main effects for mean differences nor the interaction was significant, however, Factor A: $F(2, 108) = 0.435$, $\eta_p^2 = .008$; Factor B: $F(3, 108) = 0.230$, $\eta_p^2 = .006$; interaction: $F(6, 108) = 0.811$, $\eta_p^2 = .043$.

The results indicate that the grand mean of $S_E = 1.365$, 95% confidence interval (CI) = [−0.602, 2.126], would apply to all combinations of diagonal and off-diagonal values tested for groups of four. These results would not generalize to $S_E > |100|$. A follow-up run of 100 cases of the A3-B2 condition did not produce any instances of values greater than |100|. Thus, a reasonable estimate for the probability of values that large is less than .01.

Simulation 2: Dependent Off-Diagonals and Group Size

The concept for the second simulation study was that the high, medium, and low ranges of the diagonal would be co-dependent with limited ranges of bivariate synchronization among the off-diagonal entries. For instance, if autocorrelations were high, then there would be little room for influences from another person; thus, off-diagonals would be constrained to a smaller range. Therefore, one set of experimental conditions defined ranges of off-diagonal matrix entries that were dependent on the diagonal values (Factor C) as follows:

C1: Diagonal AR_i ranged from .90 to .99, off-diagonals ranging from $-.10 < r_{ij} < +.10$.
C2: Diagonal AR_i ranged from .50 to .59, off-diagonals ranging from $-.50 < r_{ij} < +.50$.
C3: Diagonal AR_i ranged from .20 to .29, off-diagonals ranging from $-.80 < r_{ij} < .80$.

Given that the computational model was predicated on the logic of regression analysis, the hypothesis arose that group size, meaning matrix size, would affect the average value of S_E coefficients. In ordinary multiple linear regression, a trivial variable produces a nominal increase in multiple R. Thus, another comparison was made among group sizes (Factor D) of 4, 8, 12, and 16 members.

The experimental design was fully crossed once again, with 10 replications for each combination of conditions. There were two cells, C2-D8 and C3-D16, that contained outlier values >|100|. They were replaced with new samples of 10 that did not contain an outlier.

Levene's test of homogeneity of variance among the 12 cells was significant, $F(11, 108) = 3.200$, $p < .001$. Thus, any apparent differences in means might result from differences in variances. However, neither of the main effects for mean differences was significant: Factor C: $F(2, 108) = 0.744$, $\eta_p^2 = .014$; Group size: $F(3, 108) = 0.319$, $\eta_p^2 = .045$. The interaction effect was also nonsignificant, $F(6, 108) = 1.569$, $\eta_p^2 = .080$. Thus, the grand mean of $S_E = 0.112$ ($SE = 0.650$; 95% CI = [−1.177, 1.402]) would apply to all conditions. These results would not generalize to observed S_E coefficients greater than |100|.

A follow-up run of 100 cases from the C2-D8 condition did not produce any sync coefficients greater than |100|; thus, the odds of such an outlier are less than .01. However, a follow-up run of 100 cases from the C3-D16 condition did

Table 3. Descriptive Statistics for Simulation 2: Co-Dependent Diagonals and Off-Diagonals With Group Size.

Diagonal–off-diagonal condition (C)	Group size	*M*	*SD*	*n*
1	1	0.014	0.008	10
	2	0.025	0.008	10
	3	−1.539	9.317	10
	4	0.062	0.010	10
	Total	−0.360	4.523	40
2	1	1.240	0.939	10
	2	0.029	1.358	10
	3	−1.539	9.357	10
	4	−1.863	13.560	10
	Total	0.053	8.043	40
3	1	−1.436	5.143	10
	2	3.522	12.476	10
	3	2.279	4.574	10
	4	0.556	6.777	10
	Total	1.230	7.812	40
Total	1	−0.060	3.118	30
	2	1.191	7.189	30
	3	−0.267	7.983	30
	4	−0.415	8.512	30
	Total	0.112	6.968	120

produce two such outliers; thus, the odds of such an outlier are .0273. Table 3 contains the descriptive statistics for the specific conditions in Simulation 2.

An independent-samples t test between the grand means of the two samples (Factors A and B, and C and D) with unequal variances assumed was significant, $t = 1.658$, $df = 238$, $p < .05$, one-tailed. The mean synchronization value for compatible levels of on- and off-diagonal values and different group sizes (C-D) was smaller than that obtained for scenarios based on Factors A and B. The former was close to 0.00 which should be a target value for the interpretation *no synchronization*. Thus, the descriptive statistics in Table 3 are provided as an interpretive guide to synchronization coefficients drawn from plausibly real data.

Simulation 3: Matrix Dominated by Oscillators

This simulation contained one scenario, which was based on the popular assumption of pure oscillators. Pure oscillators could be fair assumptions for finger-tapping experiments or other rhythmic activities such as synchronized

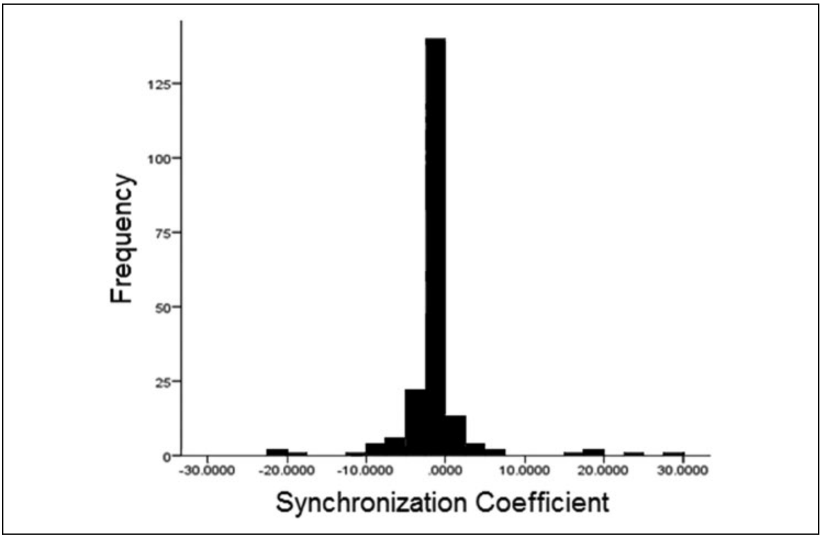

Figure 6. Distribution of S_E when relatively strong pure oscillators are assumed.

swimming or rowing. The diagonals were relatively strong negative autocorrelations ranging from −1.0 to −.5. The off-diagonals were allowed to vary from −1.00 to +1.00. The descriptive statistics based on $N = 200$ simulated cases were $M = -1.153$, $SD = 4.802$. The distribution is shown in Figure 2. It was slightly biased toward negative synchronization, although it was closely packed around the mode and symmetrical (see Figure 6).

Discussion

There is a strong and growing interest in the synchronization of physiological events in small groups and the possible implications for team performance, problem solving, and other outcomes. The synchronization of any pair of people is an NDS phenomenon, even though some research on record does not refer to those underlying principles. The principles do affect the choice of statistical models for analyzing pairwise synchronization, however, and there have been some clear advantages associated with NDS models.

The present study responded to the need for a single measure of group synchronization that does not require the restrictive assumption that the contributing time series be pure oscillators. Although pure oscillators are apparent in some rhythmic group motions, autonomic arousal has a more complex structure by virtue of the contributing neural networks, which might not be exactly the same for all team members. In fact, there is strong evidence that the low-dimensional chaos that is characteristic of self-organized systems is likely present in many cases (Guastello, 2016; Guastello et al., 2016; Guastello et al., 2006). If the medium of synchronization (e.g., autonomic arousal) is produced by the human nervous system, a self-organized system is almost guaranteed because of the large number of excitatory and inhibitory circuits that are involved (Whittle, 2010). Furthermore, a team action might in fact require its members to do different things in a coordinated fashion; the arousal levels, however, could still reflect a pattern of synchronization. It was, thus, important to develop the S_E coefficient developed here to be flexible with regard to contributing dynamics. S_E also produces some intermediate calculations that identify drivers and empaths within a group, which have other uses.

There is a loose similarity between the logic behind the S_E calculation presented here, and the logic behind generalizability theory (Cronbach, Rajaratnam, & Gleser, 1963), which was an extension of Cronbach's alpha and some intervening ideas about person perception. In generalizability theory, there are different perceivers (raters) and persons being perceived on rating scales (ratees), resulting in a rectangular matrix of ratings. One then uses the calculations from the ANOVA to assess variance among ratees, which should be relatively high, and variance among raters, which should be relatively small. The variance among raters should be relatively small due to their differing opportunities to see different aspects of the ratees. Then, there is the total amount of error variance that is not explicitly associated with either axis of the matrix, which determines the overall reliability (generalizability) of the rating system.

Kenny (1994) extended the person perception concepts behind Cronbach et al.'s work to produce a matrix-based array of perceivers and persons perceived that would result in an assessment of how much variance reflects similarities among people that one would expect from a cohesive and homogeneous group, and how much variance reflects individual differences. The scenario in which perceivers are not rated and ratees do not give ratings produces a rectangular matrix similar to those used in applications of generalizability theory. The scenario in which everyone rates everyone else is considered much more complicated to compute. In the latter case, the matrix is square and asymmetric, and there is no diagonal.

It should also be mentioned that Kenny's (1994) system was not a time series, although he indicated that results from discrete time intervals could be compared. The SYMLOG system (Bales & Cohen, 1979) of group evaluations also reflected this static-but-repeated perspective. Bales (1999) later extended the principles behind SYMLOG to continuously evolving groups with formal nonlinear dynamics operating, particularly self-organization (Pincus & Guastello, 2005).

The S_E coefficient presented here was not derived directly from Cronbach et al. (1963) or Kenny (1994), who were not studying synchronization, but rather extended from the more classical multiple linear regression theory. Unlike the classical scenario, however, the data matrix is square, the observations are continuous, and the diagonal in the matrix does not contain 1.0 except, perhaps, on rare occasions. The matrix entries are autocorrelations and semi-partial time series correlations rather than raw observation values. These computational elements prevent spurious synchronization, which could happen if two people are coincidentally acting the same way over time without having any direct interaction with each other.

Extreme Conditions

Simulation 2 showed that the population value of S_E hovers around 0.00 meaning that no synchronization exists within the group when autocorrelations and linkage coefficients exist in what are regarded as plausible conditions. Negative values are possible, which would indicate that the system is tilted toward out-of-phase relationships or inhibitory relationships among the group members (Simulation 3). More extreme (absolute) values are possible (Simulations 1 and 3), and the extreme nature of some values can be attributed to combinations of low diagonal values and high off-diagonal values.

The extreme conditions are possible when random numbers are generated, but are much less likely when the probability structures associated with real living systems are involved. A very low self-consistency combined with a very high responsivity to group members would be highly unstable overall, as it would indicate capricious group behavior and minimal individual control over entropic conditions. The personal experience in such a context would likely result in self-organizing efforts to maintain personal predictability. One might expect someone in the group to assume the role of the driver and assert some control for better or for worse. Alternatively, one might expect that an outside agent, such as law enforcement (also represented by the heavy black dot in Figure 1), might exercise control and serve as the driver.

Although the efficacy of controlling extreme crowds depends in part on the size of the crowd, the S_E coefficient itself is not affected by group size. Specifically, this study examined groups ranging in size from four to 16 members and found no significant difference in the S_E coefficient due to team size. This is a welcome departure from what one would expect from a matrix calculation that parallels that of multiple linear regression. Researchers might eventually find that connections between group size and synchronization can attribute differences in S_E to the social conditions rather than artifacts of the metric itself.

Practical Use of S_E

The matrix calculations that produce S_E would be very time consuming if performed by hand, particularly if groups larger than three members were involved. Thus, we have developed a computer program, SyncCalc 1.0 (Peressini & Guastello, 2016). To operate it, the researchers must first assemble an input matrix that is formatted like the ones shown in Tables 1 and 2. The diagonal and off-diagonal elements would come from analyses of pairwise linear (Equations 5 and 6) or nonlinear (Equations 2 and 4), which can be calculated with commonly available statistical software.

An unresolved issue concerns the relative merits of using linear versus nonlinear model coefficients to compose the synchronization matrix. The answer is likely connected to the physiological measurement, the task, and the time horizon over which group events would occur. Sometimes the nonlinear models are more accurate in terms of R^2 than the linear models for dyadic interaction (Guastello et al., 2006). Sometimes the linear models are more accurate, but the nonlinear coefficients detect important events or dynamics that the linear coefficient cannot detect. For instance, it is unlikely that electrodermal responses for a group would go into true phase lock when the surrounding events increase in speed. It has been reported, however, that greater synchronization in dyads was obtained when the pace of the task increased rather than decreased (Guastello, 2016); this difference was detectable with the nonlinear coefficients, but not with the linear ones.

Researchers need to make some choices regarding the lag length in the time series when calculating the pairwise models. In principle, physical processes require some time for the effect of one variable (person) to have an effect on another. The best choice would reflect this physical process, and the task or context could have a strong influence. Lag lengths of 1, 5, 6, and 20 s have been reported for GSR data (Guastello, 2016; Guastello et al., 2016; Guastello et al., 2015). Although a comparison of the various means for determining lag length are beyond the scope of this article, principles and procedures are discussed in the previous references.

Ergodicity, also known as stationarity, is another challenging issue in time series analysis. A time series is stationary if the dynamics (relationships among variables or people) remain constant throughout the time series. Nonstationarity can be induced by transient events, or by changes that can be attributed to control parameters within the system (Gregson, 2011, 2013; Rabinovitch, Huerta, Varona, & Afraimovich, 2008). Examples might include somebody joining or leaving the group. There could be metastable processes in which group interaction schemata self-organize and reorganize over time, possibly in relationship to external conditions (Castillo, Kloos, Holden, & Richardson, 2015; Kello & Van Orden, 2009; Kelso, 1995). Gregson (2011) noted that, within individuals, multiple neurocognitive processes are operating simultaneously, but the expression of any of them in consciousness is serial; one idea has to wait for another. A similar process occurs in group discussions; individuals process ideas simultaneously, but typically one person speaks at a time, and as a result, some do not speak as much as they would like to do. This particular phenomenon has surfaced as *time sharing demand* (Helton, Funke, & Knott, 2014).

According to Poole (1981), groups usually go through a series of developmental phases, but not all groups follow the same course of development. Another source might arise from punctuated equilibrium effects where a group self-organizes its social, communication, and work patterns sharply as it matures and moves toward its goal (Gersick, 1988). R^2 values would drop to the extent that the time series is not stationary. Ideally, researchers should try to connect changes in autonomic arousal dynamics to supervening processes.

Future Directions

New research with S_E can proceed in two groups of directions. One concerns the formal properties of the S_E itself, and the other involves connections with external events or conditions such as group performance and decision-making behavior.

The S_E coefficient is based on a matrix that is composed of values from different sources, such as different pairs of people. The prototype scenario was that all members of the group were likely to interact homogeneously, which should minimize stress on the assumptions of the calculation routine. If homogeneity of interactions cannot be assumed, however, then the new question becomes whether S_E of a given value (e.g., .50) has the same meaning if the whole group is working on the same task or the group contains subgroups working on separate subtasks that are meant to coordinate together. Extensions of the calculations might be needed to identify such bifurcations. Alternatively, S_E might be further refined to produce a number that has equivalent meaning for bifurcated and homogeneous groups.

Regarding the substance of synchronization, there are presently no psychological rules to define when synchronization is beneficial or not, but one can make some informed speculations for future research in this area. We are particularly concerned with the level of Emotion 1 (E1), homeostatic-adaptive responses generated by the autonomic or endocrine systems (Buck, 1997). Also much of the communication that is transpiring in our simulated situation occurs at the level of symbolic communication, not spontaneous communication, which is typically associated with E1 processing (Buck, 1997).

Although our measure of group synchronization is indeed taken at the low level of E1 processing, it is not limited merely to measuring E1-level spontaneous communication. The possibility of such a level-transcending measure residing at this low level, that is, of not merely being a function of (and therefore, about only) spontaneous E1 communication is compatible with, and in fact predicted by, Buck-style models of communication. Such models understand that the processes that make up the emotional, cognitive, and social "readout systems" (Buck, 1997, p. 316) are deeply inter-connected by inter-level and inter-system feedback, control, and suppression relations. Thus, even autonomic responses, when considered in a socially embedded and functioning individual must be understood holistically as potentially a function of the entire social system. Therefore, the ensemble of GSR time series of participants in such a social setting do plausibly contain information rich enough to measure synchronization of higher level functioning, including symbolic communication—and is not limited a priori to contexts in which spontaneous communication (e.g., therapy sessions) dominate. It will of course be a rich and open empirical question as to which types of groups synchronization measures are best suited.

When coordinated action is needed, one would surmise that synchronization would be high for effective groups. If a problem-solving event is involved, however, some independent thought and action could be more beneficial. Group think and group polarization have not been studied from the perspective of synchronization, but there are intermediary constructs that could bridge the theoretical gap.

The explanation of individual participation in group discussion, or more elaborate activities, has been ongoing for decades. At the individual-to-group level of analysis, game theory (von Neumann & Morgenstern, 1953), particularly the stag hunt game, individuals choose whether to join the group or act independently depending on the relative efficacy of the group versus the efficacy of their own initiatives for producing results. From the group's perspective, its effectiveness depends on enough people contributing enough effort simultaneously.

Differential participation in the group has been interpreted as *social loafing* (Latané, Williams, & Harkins, 1979). Differential participation is not always a result of loafing, but can be a result of poor group coordination (Comer, 1995; Guastello, 2009). Social loafing, furthermore, has been interpreted as a negative type of coordination inherent in stag hunt games. The ebb and flow of participation in the ongoing group activity can be traced to the ebb and flow of the group's apparent efficacy at any given point in time (Guastello & Bond, 2004; Guastello, Marra, Castro, Gomez, & Perna, in press).

The decision to participate in a group discussion at some level of involvement results from expectations of the other members' performance or efficacy (Balkwell, 1991). Expectations derive from pairwise interactions among group members as they estimate and compare the performance efficacy of the other individuals. One can then frame the group's expectations as a matrix of who or what idea dominates whom or alternative ideas. Differential participation then reflects a hierarchy of expectations regarding perception of the competence of other group members. Power and influence dynamics could be operating simultaneously with evaluations of competence: Some group members are likely to change views in response to the influence attempts of their group members whereas others stay with their initial position on a topic.

The formation of expectation states could be a complex process. It would take some time to evolve and could be complicated further by the group members' task or collective orientations (Correll & Ridgeway, 2006; Davis, 1973; Stasser, 1999). In social decision theory, a known probability distribution of individual preferences of the possible group responses is compared with all possible distributions (or a theoretically interesting subset), which correspond to *social decision schemes*; the probability distribution of individual preferences can then be compared against the predicted distributions associated with the social decision schemes (Laughlin, 2011). The broad objective for present purposes, however, is to determine how synchronization is related to these intricate group dynamics. Levels of synchronization could possibly vary by the level of collective orientation or affiliation motivation within the group (Helm, Sbarra, & Ferrer, 2012; Lumsden, Miles, Richardson, Smith, & Macrae, 2012; Vink, Wijnants, Cillessen, & Bosman, in press), or competition dynamics (Fallani et al., 2010). The S_E coefficient produces weights measuring the connection between individuals and the empath. The role of those weights to expectation processes, the formation of hierarchies, and other group dynamics are yet to be determined.

There is some preliminary evidence indicating that the driver–empath distinction can be informative (Guastello et al., 2016). In an experiment involving groups of three or four members playing an ER game, drivers were the most anxious members of the group and those less likely to participate in group decision making and expressions of leadership. Greater participation came from the empaths and whoever else was more likely to talk to the empath. Dominance issues, which on the surface would appear related to drivers' behavior, could be explored further in groups with these constructs. Similarly, anxiety issues, which were prominent among the drivers, should also be explored further as they are likely to affect the tenor of the entire group's processes.

In conclusion, the early writers were quite correct that nonlinear processes abound in group dynamics. Hopefully, the development of the synchronization coefficient can propel those investigations further with an eye toward an integrated theory of group dynamics, communication, and performance. It would eventually be helpful to consider how different types of group data lend themselves to different types of sequence analysis that have been proposed in other contexts (Cornwell, 2015; Gottman & Roy, 1990; Magnusson, Burgoon, & Casarrubea, 2016) and to then consider how different data and analytical strategies can identify underlying nonlinear processes (Guastello & Gregson, 2011), particularly when qualitative and categorical data are used in conjunction with synchronization phenomena.

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Notes

1. Raw observations X_i are transformed to z by subtracting the lower limit of X (lowest observed value) and dividing the result by the standard deviation of X. For further background on the use of location and scale values in nonlinear modeling, see Guastello and Gregson (2011).
2. The inclusion of extraneous elements in a nonlinear regression model could compromise the apparent significance of a theoretically meaningful term. Of further importance when interpreting results, including an extraneous term could actually make the R^2 go down, unlike what happens with multiple linear regression. For further explanation of the differences between the two types of regression procedures, see Guastello and Gregson (2011).
3. An autocorrelation function can become nonlinear for various reasons such as autocorrelation of residuals, dependent errors of other forms, and a multiplicity of lag terms (Guastello & Gregson, 2011; Ozaki, 2012). The number of lag components can increase considerably in models containing two or more time series; the larger the number of parameters, the smaller the chance for replicating the model on another data set.

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