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Capturing non-linear temporally embedded processes in organizations using recurrence quantification analysis

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ABSTRACT
Despite the growing consensus that the majority of psychological phenomena at work are temporally embedded and highly dynamic, existing research is often based on simplified theoretical and methodological models, which take limited account of process dynamics and especially non-linear growth trajectories. In this paper, we highlight the potentials of using recurrence quantifications analysis (RQA) and an extension of RQA – cross-recurrence quantification analysis (CRQA) – for researching process dynamics in organizations. (C)RQA is a powerful technique that can be used to both visualize and quantify time-series data such as repeated measurements of psychological states or sequentially coded dyadic and team interactions. To illustrate the manifold opportunities of (C)RQA, we present three application examples focusing on individuals as systems, dyads as systems, and teams as systems. Specifically, we highlight how (C)RQA can be applied to individual diary data, to leader-follower communication dynamics observed during annual appraisal interviews, and to high-density coded team interactions observed during organizational meetings. We discuss the strengths and limitations of (C)RQA and provide recommendations for researchers interested in using the method.

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Organizational scholars increasingly agree that cross-sectional research and the associated assumptions of stability and mostly linearity fall short in capturing the complexity of organizational phenomena in contemporary organizations. Interest is growing to model and understand the change dynamics that are at the core of many organizational phenomena (e.g., Herndon & Lewis, 2015; Hofmans, Vantilborgh, & Solinger, 2018; Lehmann-Willenbrock & Allen, 2018). This trend has gradually resulted in a shift from differential to temporal process research as exemplified by several theoretical pieces in the organizational and team literature (e.g., Ancona, Goodman, Lawrence, & Tushman, 2001; Cronin, Weingart, & Todorova, 2011; Langley, Smallman, Tsoukas, & Van de Ven, 2013; Roe, 2008; Roe, Gockel, & Meyer, 2012).

For example, recent research has looked into the change trajectories of organizational commitment (Ng, Feldman, & Lam, 2010; van Olffen, Solinger, & Roe, 2016) and affect at work (Knight, 2013), leadership scholars called for more efforts directed at how dyadic leader-follower relationships evolve over time (Bluedorn & Jaussi, 2008), and team research sees an upsurge in studies focussing on interaction processes unfolding in teams (e.g., Lehmann-Willenbrock & Chiu, 2018; Lei, Waller, Hagen, & Kaplan, 2016). To put it in a nutshell: many organizational phenomena are inevitably linked to time and context.

This shift towards a more dynamic perspective on organizational phenomena is promising in terms of what we can learn about individual experiences at work and the interactions that drive teamwork in organizations. However, it also challenges how we think about organizational phenomena and, ultimately, how we study them. It is still the exception rather than the norm that ideas of dynamism and non-linearity – increasingly inherent in the conceptualization of psychological phenomena at work – are also reflected in empirical research.

To tackle this dynamic perspective, appropriate and innovative methods are needed that can address the specificities of dynamic process data (Kozlowski, 2015; Lehmann-Willenbrock & Allen, 2018). In this paper, we focus on one very promising non-linear method that is slowly starting to gain momentum in organizational research (e.g., Gorman, Cooke, Amazeen, & Fouse, 2012; Knight, Kennedy, & McComb, 2016), namely recurrence quantification analysis (RQA) and its extension *cross*-recurrence quantification analysis (CRQA). The overall aim of the present paper is to show how (C)RQA can help to visualize and quantify process dynamics, thus moving away from a more traditional, chain-like, and linear view on organizational phenomena.

We first draw from previous theorizing on complex adaptive systems to provide a brief discussion of how a non-linear perspective can advance our understanding of temporally embedded processes unfolding within and between individuals, dyads, and teams. Second, we describe the principles of (C)RQA, cover central measures, and highlight initial studies that utilized (C)RQA. Third, to further illustrate the potentials of (C)RQA and to aid the implementation of this method in organizational research, we provide exemplary data from three different application contexts. We show how (C)RQA can be applied (a) to diary data capturing within-person changes (here: repeated measurement of affect over the

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course of 22 weeks), (b) to dyadic leader-follower communication dynamics (here: mutual alignment in word use), and (c) to coded team interactions (here: recurrence of verbal behaviour observed during regular team meetings). Interested readers can find the accompanying detailed R code and a subset of data via the Open Science Framework https://osf.io/xe8hw/?view_only=27cd218b5f0d4a419b5c347cdfd8cfd0. We close with a discussion of the implications and limitations of using (C)RQA for organizational research and outline recommendations for researchers interested in using the method.

Change and recurrence in complex adaptive systems

Organizational members do not exist in a social vacuum (Katz & Kahn, 1978): Instead, our affective states and emotions, cognitions and motivations, and, ultimately, our overt behaviour are dependent on our current surrounding environment and previous experiences. As a result, organizational members have been described as complex adaptive systems that dynamically change over time and evolve as they interact with one another and the embedding context they find themselves in (Arrow, McGrath, & Berdahl, 2000; Kozlowski & Ilgen, 2006; McGrath, Arrow, & Berdahl, 2000; Ramos-Villagrasa, Marques-Quinteiro, Navarro, & Rico, 2018). In order not to overload the focus of our article, we concentrate on individuals, dyads, and teams as systems but acknowledge that the broader management literature also considers entire organizations as complex adaptive systems (e.g., Dooley, 1997; Schneider & Somers, 2006).

Defining complex adaptive systems

Looking at organizational life from a dynamic systems perspective requires clarifying what defines a system. Following the tradition of dynamic systems theory (Alligood, Sauer, & Yorke, 1996; Thelen & Smith, 1998) and chaos theory (Gleick, 1997; Thiétart & Forgues, 1995), a system is a collection of interacting elements or components that dynamically change over time. To illustrate, take a supervisor and a subordinate in a spatial environment (e.g., a team meeting) with various affective, cognitive, motivational, and behavioural variables that characterize this particular leader-follower dyad and their relationship at a particular point in time. Such a system is *complex* because of the intricate interdependencies among these interacting elements (Arrow et al., 2000). For example, previous research disclosed that supervisors' relation-oriented statements can elicit active employee involvement during face-to-face conversations, manifesting in repeating communication patterns (Meinecke, Lehmann-Willenbrock, & Kauffeld, 2017). In addition, if an employee has had a difficult relationship with a supervisor in the past, this will likely affect his/her implicit expectations and assumptions of good leadership and also shape how actively that employee participates in conversations with his/her (new) supervisor (cf. Offermann, Kennedy, & Wirtz, 1994). Thus, the complex interplay of the interacting elements of the system affects, in our example, how the conversation unfolds and is reflected in the structure of the conversation.

This example further demonstrates that a system itself consists of smaller systems (e.g., experiences nested in individuals; individuals nested in dyads). Moreover, complexity refers to systems interacting with other systems, both with systems of their own size (e.g., teams collaborating with other teams) as well as with larger "parent" systems (e.g., teams nested in organizations). Thus, a system forms a *hierarchical structure*, which constitutes another defining property of complex systems (McGrath et al., 2000; van Geert, 2011).

The latter further emphasizes that systems are embedded in a surrounding social context. They are not static, isolated sets of elements but are rather characterized by fuzzy and permeable boundaries. As such, systems respond and adapt to changes in their environment (e.g., situational demands for higher workload) and can be further described as *open* and *adaptive* (Arrow et al., 2000). A change in leadership, for instance, may disrupt employees' individual motivation, deteriorate leader-follower relationships, and lower team cohesion. A more positive example would be successful team adaptation in the context of crisis management (e.g., Lei et al., 2016).

Defining recurrence

Despite this complexity and dynamism inherent in the conceptualization of individuals, dyads, and teams as complex adaptive systems, they tend to not operate in a completely random fashion. Instead, they can be arranged on a continuum, ranging from orderliness (i.e., deterministic) to randomness (i.e., nondeterministic, e.g., van Geert, 2011). The underlying premise of this line of thinking is that a system can only be in one state at a given moment in time. As time unfolds, certain states are visited again and recurrent patterns develop, leading to stability. The term *recurrence*, in particular, describes that the system's trajectory returns to a state it has visited before. The development of recurrent patterns is described as *self-organization* or emergence in complex adaptive systems – a process that is often spontaneous, difficult to predict, and non-linear in nature (Guastello, 2001; see also Fulmer & Ostroff, 2016; Kozlowski, 2015; Waller, Okhuysen, & Saghafian, 2016). The particular time scale on which these recurrent properties emerge is flexible and dependent on the specific research question under investigation, ranging from moment-to-moment conversational dynamics to years (van Geert, 2011).

The recurrent qualities that result from self-organization are conceptualized at a higher level and cannot be simply reduced to the sum of the system's individual elements (Guastello, 2001). Yet, we can carefully track the system's trajectory from state to state, capturing its dynamic movement. The quantification of these recurrent structures enables an enquiry on the characteristics of individual, dyadic, or team dynamics.

In empirical research, organizational scholars will likely find themselves to struggle with this complexity, but the conceptualization of organizational phenomena in the context of complex systems can help reorient the field and inspire researchers to adopt a new logic of enquiry (cf. McGrath et al., 2000). The challenge then is to make these recurrent patterns tangible and to ground them in adequate process theory, specific to the research question at hand.

A dynamic systems lens on individuals, dyads, and team

Looking at individuals as complex adaptive systems, we can extrapolate from influential theoretical and empirical work in neighbouring fields of organizational science, specifically developmental psychology (Guastello, 2001). While it might still seem unusual to organizational psychologists to think in terms of process (rather than in terms of differential differences) and to make specific assumptions about the change dynamics of individual experiences of affect, cognition, motivation, and behaviour at work, this approach is central to developmental psychology (Guastello, 2001; van Geert, 2011). It is fundamentally assumed that people go through qualitatively different stages of development across the lifespan. This focus on temporality and individual change is increasingly being discussed by organizational scholars. For example, van Olffen et al. (2016) recently outlined how commitment to the organization should be explored from a temporal perspective focusing on committing trajectories and the patterns inherent in them. For instance, does commitment increase steadily after joining the organization and then remain stable at a certain level (i.e., values are not random but to a certain degree repetitive)? And is this process different for different employees? Good process theory that accounts for trajectories in commitment and related organizational phenomena is then pivotal in order to describe typical trajectories, yet, currently, such theoretical models are largely missing (cf. Solinger, van Olffen, Roe, & Hofmans, 2013). From a methodological point of view, it is emphasized that repeated measurements of high density are necessary to trace such individual trajectories (van Olffen et al., 2016).

A case for conceptualizing dyads as complex adaptive systems can be found in the literature on leader-follower dynamics (Boal & Schultz, 2007; Uhl-Bien, Marion, & McKelvey, 2007). For example, leadership scholars have repeatedly argued for a stronger focus on leadership as a social influence process in which followers – in addition to formal leaders – play a central role (Uhl-Bien et al., 2007; Uhl-Bien, Riggio, Lowe, & Carsten, 2014). Thus, leadership should not (only) be understood as a position but rather as "a complex interplay from which a collective impetus for action and change emerges" (Uhl-Bien et al., 2007, p. 299). As such, several interacting forces are at play that shape leadership influence *in situ* in contemporary organizations. Again, non-linearity and sudden fluctuations have been discussed to characterize change, e.g., resulting from build-up tension (Uhl-Bien et al., 2007).

Finally, the dynamic systems perspective on teams has received increased attention since around the turn of the century (Arrow et al., 2000; McGrath et al., 2000). Central in this respect is a temporal view on teams, emphasizing that teams mature and develop as time passes. This change does not follow a linear, perfectly predictable pattern (e.g., Arrow, 1997). Instead, teams can go through "metamorphosis" (McGrath et al., 2000, p. 98), meaning that teams can show breaking points and change rather radically. Hence, team process dynamics challenge traditional ideas of determinism and linearity (Kozlowski, 2015). In order to gain deeper insights into the way team processes dynamically unfold over time and give rise to team-level dynamics, time-sensitive measurements are needed – especially those that have a higher sampling rate (Kozlowski, 2015).

Thus, in addition to building adequate theory that accounts for the dynamics of organizational phenomena, suitable measurements are needed that allow to collect time-sensitive data and that capture how fine-grained states and interactions temporally unfold in individuals, dyads, and teams. Analysis techniques that can handle and process high granularity time-series data and that disclose non-linear trajectories and critical changes in trajectories are needed. Echoing and expanding on initial arguments set forth in the team literature by Knight et al. (2016), we argue that RQA offers such possibilities and complements (or may even take the place of) traditional linear modelling.

The tenets of recurrence quantification analysis

RQA is an approach originally developed in the field of system dynamics to study the patterns of change in non-linear systems (Eckmann, Oliffson Kamphorst, & Ruelle, 1987; Webber & Zbilut, 1994, 2005). RQA first and foremost set out as a technique to visualize changes in dynamic systems over time by means of *recurrence plots* (Eckmann et al., 1987; Marwan, 2008). Recurrence plots illustrate graphically how a system revisits similar states at different points in time. The basic idea behind recurrence plots is that repetitive sequences can be recognized with the naked eye, disclosing how stable, predictable, and complex a dynamic system is (Marwan, 2011; Marwan, Romano, Thiel, & Kurths, 2007). In terms of data requirements, RQA is applicable to time-series data and can be used on both categorical time-series data, as in our examples below, as well as continuous time-series data. For continuously sampled signals such as physiological systems data (e.g., heart rate), additional steps need to be taken to convert the data into meaningful recurrence plots (see Marwan, 2011).

To showcase the possibilities of recurrence plots, we want to start with an illustrative example. Specifically, our example is based on a snippet of the well-acclaimed song "I Like to Move It" by Reel 2 Real. This particular song is characterized by a considerable amount of recurrence and a rhythmic pattern. A similar procedure for describing RQA can be found in Wallot (2017). For illustration purposes, we will first zoom in on the following part of the song: "I like to move it, move it. I like to move it, move it. I like to move it, move it. Ya like to move it." As unit of analysis, we focus on each individual letter. By removing the spaces and punctuation, the sequential order of the individual letters is revealed. In our example, this string of letters is 71 characters long and consists of a total of ten different letters: "ILIKETOMOVEITMOVEITILIKETOMOVEITMOVEITILIKETOMOVEITMOVEITYALIKETOMOVEIT".

This string of letters can then be converted into a recurrence plot, with each letter representing a single time step. Figure 1 shows this exemplary recurrence plot. On the *x*-axis, we placed the 71 letters from left to right, and on the *y*-axis, we placed the same 71 letters from bottom to top. The shaded black areas indicate that the system revisits a previous state. These are called

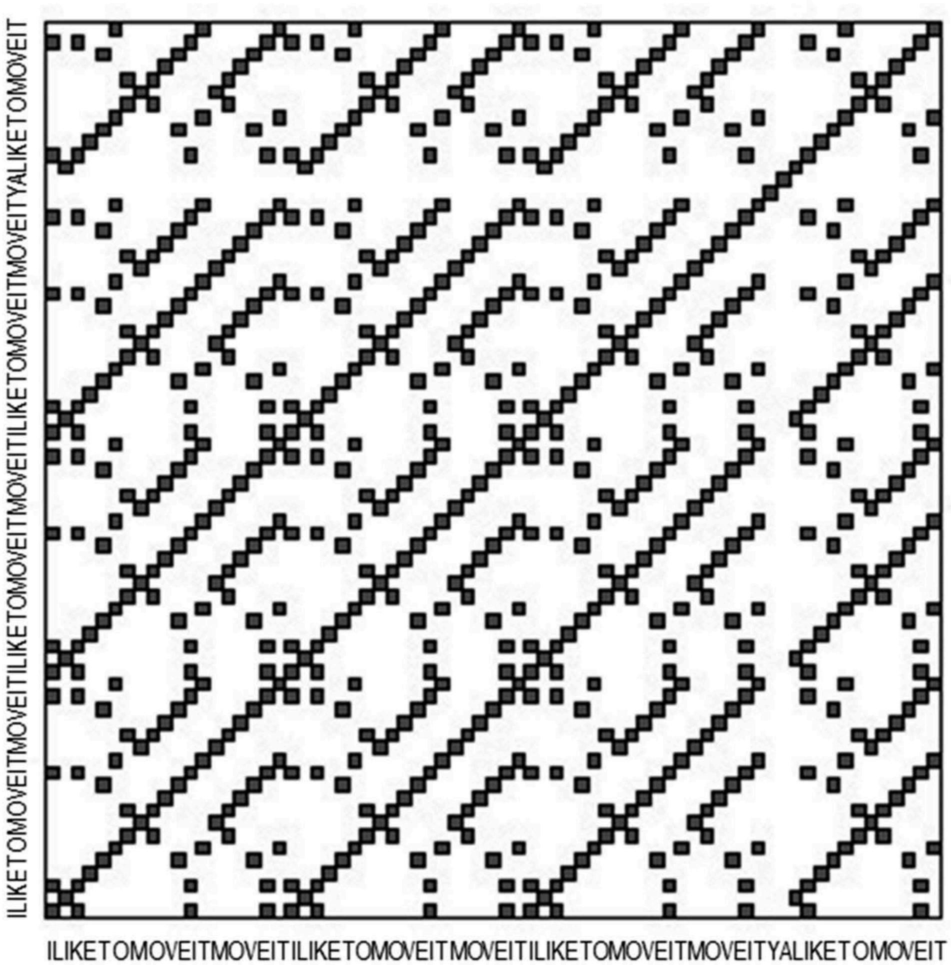

Figure 1. Example recurrence plot across the first 71 letters of the song "I like to move it, move it" by Reel 2 Real. Shaded black areas denote recurrence.

recurrence points. In our example, this means that a particular letter has been used again. For example, the letter "M" occurs a total of seven times (on positions 8, 14, 27, 33, 46, 52, and 66). As typical for recurrence plots of a single system, our example is symmetric across the diagonal, and the diagonal is marked as recurrent, thus it appears black. The pattern of the shaded black areas around the diagonal reveals the periodic nature of the song. Recurrences of longer sequences of repeating letters are shown as diagonal line structures.

Quantifying recurrent patterns

Although a qualitative visual inspection of recurrence plots is very useful for getting an overview of non-linear recurrent patterns such a visual "reading" becomes increasingly time-consuming and cumbersome when working with larger recurrence plots and larger samples in general. RQA thus goes beyond mere visual inspection and provides measures to quantify the repetitive properties of dynamic systems (Marwan et al., 2007; Webber & Zbilut, 1994). These measures help to compare recurrence plots across different systems (e.g., teams whose interaction dynamics were analysed using the same coding system) as well as within a system (e.g., one team that has been analysed in different ways, including heart rate and communication).

The measures available for the description of recurrence plots are manifold and tap different features of recurrence such as stability and complexity in recurrence (Marwan et al., 2007; Wallot, 2017; Webber & Zbilut, 1994). Since the measures are all based on the graphical visualization (i.e., the recurrence plot), many show considerable conceptual overlap. From our experience, this goes hand in hand with the fact that some of the measures are highly correlated. Although tempting to the researcher, measures should not be selected depending on how well they perform in subsequent statistical analyses. It is rather the researcher's challenge to focus on those measures that best fit the current research question at hand. In the following, we want to focus on three commonly used measures, namely recurrence rate, determinism, and the average diagonal line length. An overview including additional measures is provided in Table 1.

Recurrence rate is a key measure for describing how intensely a system revisited previous states. The standard definition defines recurrence rate as the sum of all recurrence points (i.e., shaded black areas) divided by the sum off all points in the recurrence plot (Webber & Zbilut, 1994). Thus, recurrence rate is the percentage of recurrence points in the plot. The higher the recurrence rate, the more the system repeats itself. For an outside observer, this can reduce complexity as it enables to observe patterns. Our example in Figure 1 depicts a 71 × 71

Table 1. Selection of classical recurrence measures (Marwan et al., 2007).

Measure	Definition	Illustration
Measures based on density		
Recurrence rate (REC or RR)	Percentage of recurrence points in the recurrence plots	How often does the system show the same behaviour (i.e., how repetitive is the time series)? Describes the density of recurrence. E.g., if a team shows unique behaviour at every time step throughout a meeting, REC will be zero. If a team asks several questions during the meeting, REC increases.
Measures based on diagonal lines		
Determinism (DET)	Percentage of recurrence points that are part of a diagonal line structure (i.e., adjacent recurrent points)	To what extent do repetitions occur in sequences of recurrent events? Describes the predictability of the system. As opposed to single, isolated recurrence points, recurrence can be part of a sequence. E.g., conversational routines such as "question→answer" sequences during a team meeting
Ratio (RATIO)*	Ratio between determinism and recurrence rate	What is the relationship between determinism and recurrence rate? This measure can be useful to detect transitions in a time series. E.g., when a team meeting is characterized by low determinism (but high REC) in the first half of the meeting and high determinism (and still high REC) in the second half of the meeting this would signalize that the team took some time to settle into a routine
Maximum diagonal line length (Lmax or maxL)	Length of the single longest diagonal line structure in the recurrence plot	How long is the longest uninterrupted repeating sequence? Hints at divergence in the trajectory. E.g., a repeating sequence of "problem → problem analysis → solution → solution analysis → agreement" describes a rather sophisticated behavioural pattern.
Average diagonal line length (Lmean)*	Length of the average diagonal lines in the recurrence plot	How long is the average repeating sequence? Describes the extent to which the system is structured. E.g., repeating short sequences of "humour → laughter" or "question→answer" describe rather short and less complex patterns.
Divergence (DIV)*	DIV is the inverse of Lmax (i.e., 1/Lmax)	May be helpful in subsequent calculations instead of Lmax
Entropy (ENTR)	Shannon information entropy, i.e., the probability distribution of the diagonal line lengths	Describes the complexity of the deterministic structure of the system. Higher values indicate higher complexity (i.e., plurality of patterns) whereas smaller values indicate lower complexity (i.e., predominance of a single pattern). E.g., if the team shows a large behavioural repertoire of different behavioural patterns, ENTR is higher.
Measures for vertical line structures		
Laminarity (LAM)	Percentage of recurrence points that are part of a vertical line structure (analogous to the def of determinism)	Represents the occurrence of laminar (as opposed to turbulent) states in the system and allows for the investigation of intermittency. E.g., a team starts a meeting with a brainstorming session and several ideas are presented in a row; or affect is measured weekly and shows periods of stability
Maximum diagonal line length (Vmax)*	Length of the single longest vertical line structure in the recurrence plot	How long is the longest uninterrupted repeating sequence of the same behaviour? E.g., ten ideas are stated in a row; or the longest stability in affect was 10 weeks
Average vertical line length (Vmean or TT)	Length of the average vertical lines in the recurrence plot	How long is the average repeating sequence of the same behaviour? E.g., how many ideas are voiced in succession on average? how stable is affect on average?

Note. Measure are provided by the nonlinearTseries package and the crqa package in R, except where noted otherwise. In case two abbreviations are given in parentheses, the second refers to the abbreviation in the crqa package.
* Currently not part of the crqa application in R

plot, thus we can count a total of 5041 points in the recurrence plot. As the main diagonal is marked as recurrent by default, these points are not included in the calculations. Therefore, we subtract 71 from the 5041 points, resulting in 4970 points. The total number of black recurrence points is 752–71 = 681. The recurrence rate then amounts to 681/4970 = 13.70%. Although the recurrence rate is a good indicator of how repetitive the system is, the value would not change if the time-series, in our case the string of the letters, would be shuffled.

Determinism, on the other hand, takes the sequential order of the recurrence points into account and is defined as the percentage of recurrence points that are part of a diagonal line structure (not including the main diagonal). Determinism thus describes "how many individual repetitions occur in connected trajectories" (Wallot, 2017, p. 385) and, therefore, is a measure of the relative degree of random vs. deterministic structure of a time series. Higher determinism enables to make predictions regarding future patterns. Mathematically, determinism is the sum of all diagonally adjacent recurrence points divided by the sum of all recurrence points (Webber & Zbilut, 1994). Our example in Figure 1 shows a total of 681 recurrence points of which 395 recurrence points are part of a diagonal structure (again, the main diagonal is not counted). Determinism then reaches a value of 395/681 = 58%.

Finally, the *average diagonal line length* describes how long the average repeating trajectory is. In our example, the average line length is 11.5. Since this measure is not standardized, additional thought should be given when comparing this measure across different plots (i.e., dynamic systems).

After we initially looked at only a part of the song, we will now briefly turn to the entire song. Figure 2 shows the respective recurrence plot for the complete song, consisting of a total of 1853 units (i.e., individual letters). An interesting feature of the complete song is that phases of high recurrence alternate with individual rap parts that show a much higher flexibility with regard to the sequence of the individual letters. The recurrence plot highlights these non-linear shifts. Overall, we can easily identify three larger episodes of high recurrence (i.e., the "I like to move it" chorus), with a longer phase at the beginning and end of the song and a shorter phase in the middle of the song. These phases of high recurrence are offset

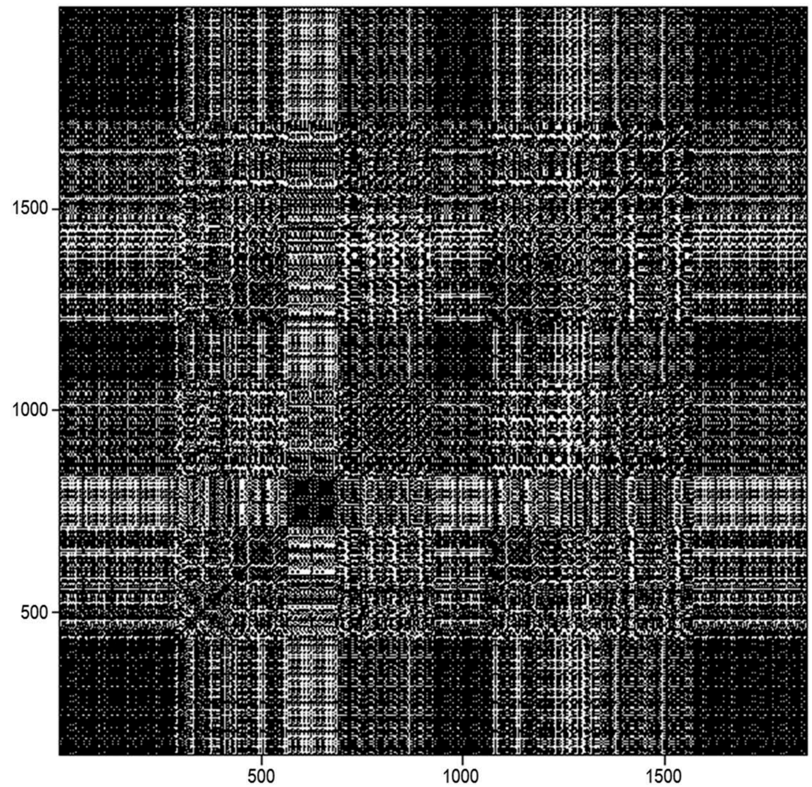

Figure 2. Recurrence plot for the entire song "I like to move it, move it" by Reel 2 Real. Each letter represents one time step (total of 1853 letters). Shaded black areas denote recurrence.

by two longer rap parts. These rap parts, albeit characterized by much less recurrence, are not completely random but show small to moderate amounts of recurrence. For example, the first rap part is characterized by a brief window of noticeable recurrence starting shortly after unit 500. We hope this example gives a first glimpse into the potential of RQA for capturing and quantifying the repetitive properties of dynamic systems, thereby shedding light on non-linear trajectories and breaking points in time-series data.[1]

An extension of RQA: cross-recurrence quantification analysis (CRQA)

CRQA is a multivariate extension of RQA and can be used to explore dependencies between two different systems (e.g., two interlocutors). Thus, CRQA requires separate information from two systems and analyses their cross-recurrence (Coco & Dale, 2014; Fusaroli, Konvalinka, & Wallot, 2014). In that sense, CRQA can be described as "a non-linear analog of cross-correlation" (Fusaroli & Tylén, 2016, p. 156). CRQA is especially suitable for research questions pertaining to dyadic dynamic systems such as leader-follower interactions or doctor-patient consultations (see also Abney, Paxton, Dale, & Kello, 2015, as well as Angus, Watson, Smith, Gallois, & Wiles, 2012).

The metrics that can be derived from CRQA are the same as those outlined above for traditional RQA (see Table 1). In addition, CRQA follows the same data requirements as RQA with the exception that two separate time-series data streams – one for each system – are required. Recurrence plots for CRQA then display the shared trajectories of the systems' behaviours. Our second application example below will specifically focus on CRQA.

Applications of (C)RQA in organizational research

(C)RQA is not yet strongly represented in organizational research but slowly starts to gain ground in specific areas. In the following, we briefly discuss selected examples to illustrate the versatility of the method. Turning to individuals as dynamic systems, RQA-applications in the broader organizational literature are still very limited. Although we can see a promising rise in studies that aim to explore individual change trajectories of organizational phenomena such as affective responses or motivation (e.g., Liu, Mitchell, Lee, Holtom, & Hinkin, 2012; Rook & Zijlstra, 2006), studies that specifically leverage the benefits of RQA are extremely scarce. Instead, it appears that psychological thinking and corresponding research methods are still largely dominated by notions of individual differences and stability, with the result that many empirical studies are still bounded within the limits of linear regression. A rare exception is a study by García-Izquierdo, Ramos-Villagrasa, and Navarro (2012) who used RQA to explore performance patterns of 94 professional basketball players over a ten-year period. They hypothesized that basketball players' performance shows low stability over time and subsequently contrasted different dynamic patterns across players. A key finding of their study was that the time series of only seven of the 94 players showed a near linear trend. The remaining time series were characterized by high fluctuations in performance over time.

An illustrative example applying (C)RQA to dyadic time-series data can be found in a study by Fusaroli and Tylén (2016). Focusing on communication in dyads, the authors explored the interplay between conversational dynamics and performance in a joint decision-making task. Participants were invited to the lab and asked to rate images presented to them on a computer screen in terms of their visual contrast. The two participants sat back to back, each in front of a computer. When they disagreed in their choice, the dyads were asked to negotiate and arrive at a joint decision. Working from transcripts of the real-time video recordings, the authors created a total of three data sets with time series for different communicational signals (i.e., lexical, prosodic, and speech/pause patterns). The authors were mainly interested in differences between *interactive alignment* and *interpersonal synergy* in conversations. Whereas the latter refers to structural organization in the form of complementary conversational patterns, interactive alignment encompasses that the two interlocutors synchronize their speech with one another. Contrasting results from RQA and CRQA, Fusaroli and Tylén (2016) found that patterns for both interactive alignment and interpersonal synergy were related to dyadic performance with structural organization pertaining to synergy showing stronger results. In sum, their study illustrates the conceptual and methodological benefits of recurrence analysis for research on dyadic human systems by highlighting the delicate communication dynamics that drive performance in dyads.

In contrast to work on individuals and dyads, our literature search revealed that (C)RQA is most commonly used in the context of teams. Initial studies show great potential of the methodology for research questions related to team functioning and team interaction processes (for an introductory article on the use of RQA for team research see Knight et al., 2016). Whereas the majority of team studies drawing on RQA take place in the lab (e.g., Gorman et al., 2012; Mønster, Håkonsson, Eskildsen, & Wallot, 2016; Russell, Funke, Knott, & Strang, 2012; Strang, Funke, Russell, Dukes, & Middendorf, 2014), Ramos-Villagrasa, Navarro, and García-Izquierdo (2012) used RQA to examine performance dynamics of 23 professional basketball teams. Analysing data across a 12-year period (i.e., 12 seasons), they explored whether more or less chaotic patterns are associated with better team outcomes. Specifically, they focused on two objective measures, i.e., a composite score that includes several performance indicators (such as number of points per game) as well as the ranking of each team at the end of each play day. Based on the sequential observations of these two measures, the authors searched for recurring patterns in the time series. In line with the dynamic systems perspective, they differentiated between those patterns that were deterministic (i.e., predictable) and those patterns that were nondeterministic, hence random. Deterministic patterns were further differentiated into (a) linear patterns, (b) non-linear patterns that were characterized by low-dimensional chaos, and (c) non-linear patterns that were characterized by high-dimensional chaos. The latter are more closely related to nondeterminstic patterns but are not fully random. Findings revealed that all teams showed fairly chaotic patterns based on the two objective team effectiveness measures. Those teams with low-dimensional chaotic patterns (i.e., non-linear but deterministic patterns) performed the best overall as indicated by the number of play-offs they participated in at the end of the season. In sum, this study provided initial evidence for non-linear trends in team performance showing that a certain degree of chaos – termed *healthy variability* – is beneficial for (basketball) teams (Ramos-Villagrasa et al., 2012).

To make the application of RQA more accessible to organizational researchers, we will now offer three application examples based on field data from individuals, dyads, and teams, respectively. The examples aim to illustrate the application possibilities of the methodology, using different data sources (i.e., individuals, dyads, teams) and process variables (i.e., repeated measurements of state affect, alignment in communication based on word use, and functional behavioural coding). Furthermore, we outline the technical implementation in R.

Application example 1: individual trajectories

Motivation and research question

Emotions can be found throughout the entire spectrum of human interactions and their contexts – also in organizations (e.g., Barsade & Knight, 2015; Knight & Eisenkraft, 2015). As postulated by affective events theory (AET; Weiss & Cropanzano, 1996), emotions in the workplace are reactions to specific events occurring in the organizational context. Emotions caused by these specific affective events, in turn, influence employees' subsequent behaviours as well as the formation of more long-term attitudes, such as job satisfaction or organizational commitment. AET ultimately claims that employees' behaviour and performance rely less on attitudes and personality but rather on emotional states caused by events in their workplace environment (Weiss, Nicholas, & Daus, 1999). These affective experiences are fundamentally characterized by their temporal dynamics (e.g., Barsade & Knight, 2015; Kuppens, Oravecz, & Tuerlinckx, 2010). In fact, affective experiences may only become salient *because* they are subject to change, enabling individuals to monitor important internal and external changes and alter their behaviour accordingly (Frijda, 2010; Scherer, 2009).

Most employees will have to face changes in their tasks, technology, and environment at some time during their work, as during the course of a project (Arrow, 1997; Arrow, Poole, Henry, Wheelan, & Moreland, 2004). In project work, critical success factors (e.g., project commitment, technical tasks, use of specific tools and technologies) have been found to change at different time points which may be explained by the project life cycle and its respective phases (Hoegl, Weinkauf, & Gemuenden, 2004; Pinto & Prescott, 1988). The phases themselves are associated with different patterns of both communication (Swigger, Hoyt, Sere, Lopez, & Alpaslan, 2012) as well as intra-team coordination (Hoegl et al., 2004). Accordingly, given that the transition from one project phase to the next has been shown to elicit changes in workplace interactions, we propose that these transitions will also function as distinct affective events. The aim of the following application example will thus be to analyse how project phase transtions are reflected in the pattern of an employee's affective states unfolding across the project's life cycle.

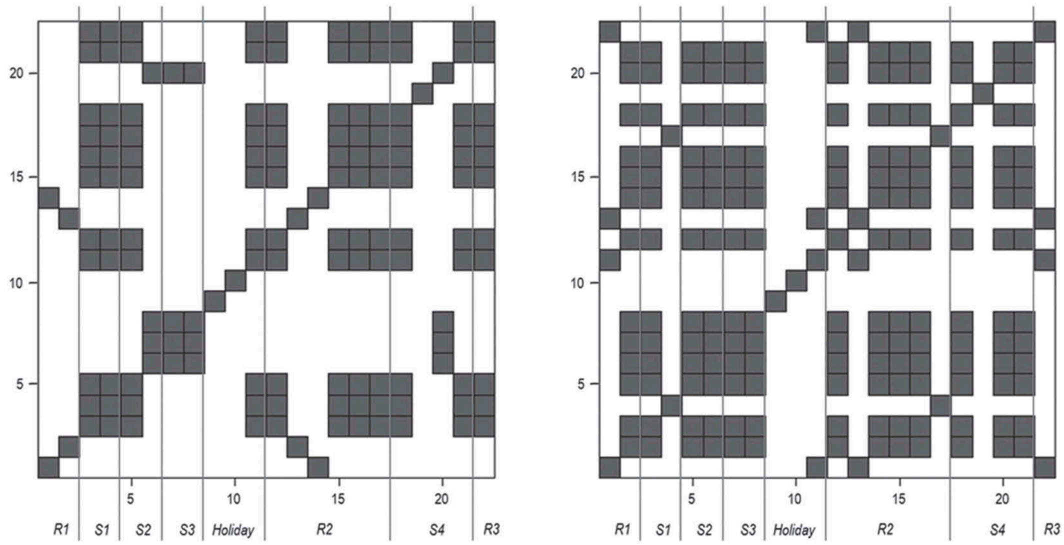

Figure 3. Recurrence plots based on repeated assessments of affect across 22 weeks (application example 1). The left plot shows the weekly reports for negative affect, the right plot shows the weekly reports for positive affect of the same individual. Shaded black areas denote recurrence, indicating that positive (respectively negative) affect was equally pronounced. R = Review and retrospection phase, S = Sprint.

Participants and procedure

Data for this first application example were sampled from six members of a software engineering team who took part in a weekly diary study over the course of a 22-week-project. Team members' age ranged from 26 to 42 years (M = 31.2, SD = 6.5). The project consisted of four iterative software development phases (called *sprints*), enclosed by three transitional *review and retrospection* phases (i.e., presenting the software to the customer and receiving feedback) as well as one intermediary holiday period (see Figure 3).

Participants were instructed to complete an online questionnaire at the end of each working week (i.e., usually on a Friday) in order to rate their momentary negative (e.g., distressed, upset, irritable) and positive (e.g., active, interested, inspired) affect. We employed a 5-point response format, ranging from 1 *(not at all)* to 5 *(very much)*, using twelve items from the PANAS scale (Watson, Clark, & Tellegen, 1988; German version by Krohne, Egloff, Kohlmann, & Tausch, 1996). Both scales showed excellent average reliabilities across all items and time points (negative affect: R_{kF} = .99; positive affect: R_{kF} = .99, for an extensive description of multilevel reliabilities see Shrout & Lane, 2012). The generalizability of within-person variations averaged over items (i.e., time points nested within people; Shrout & Lane, 2012) was acceptable for positive (R_{CN} = .73) and excellent for negative affect (R_{CN} = .91)[2]. On average, the extent of positive and negative affect over all participants and measurement points equalled to 2.36 (SD = .83, Min = 1, Max = 4) and 1.69 (SD = .85, Min = 1, Max = 3.83), respectively. For the purpose of our application example, we employed data from that team member who displayed the highest completion rate (86%).

Data formatting

To calculate recurrence, we first transformed our affect ratings into integers (i.e., by rounding up or down). Accordingly, as affect was rated on a scale of 1 (not at all) to 5 (very much), both affect variables had five potential levels. Missing data points were transformed into unique numbers in order to exclude them from recurrence detection. For the purpose of our recurrence calculations, we treated our data as categorical. That is, recurrence in weekly affective states was detected only when the exact same value was reached. We subsequently applied RQA using the software package nonlinearTseries (Garcia, 2015) in R to visualize the recurrence plots and extract quantifications for both positive and negative affect. An overview of additional software options can be found online (see http://www.recurrence-plot.tk).

As a starting point of our analysis, we focus on the *recurrence rate* as the most fundamental measure of recurrence. As elaborated above, the recurrence rate is the percentage of recurrence points (i.e., shaded black areas in the recurrence plot) of the total possible number of cells in the plot, thus describing how intensely a system revisits previous states (Webber & Zbilut, 1994).

Data analysis and discussion

Figure 3 shows the recurrence plots for both negative and positive affect. Recurrence rates were 30.6% and 39.7%, respectively. Even at first sight, the plots confirm the difference between the two rates, with the plot for positive affect appearing denser, i.e., showing more recurrence. The nature of these recurrences can be analysed by discerning between the respective rows (or columns, as the recurrence plot is symmetrical). For instance, the first affective state in the positive affect sequence reappeared three more times – twice around the middle and once at the end. Looking into our data, this characterized a slight experience of positive affect (i.e., a value of 2). The second affective state (representing a moderate degree of positive affect, i.e., a value of 3) in the time series, however, exhibited a high degree of recurrence, repeating itself another twelve times. A fairly high (value of 4) experience of positive affect occurred only twice in the sequence, shortly before sprint 2 and 4 began. Negative affective states, in turn, showed a much lower tendency to repeat themselves. For instance, both the first (fairly high negative affect, i.e., value of 4) and second (moderate degree of negative affect, i.e., value of 3) affective state in the sequence reoccurred only one more time each, both somewhere around the middle (both in the second review and retrospection phase, which marked a transitional period). The rest of the time series was characterized by a fairly even distribution of very low to slight negative affect. In sum, while our exemplary team member exhibited a fairly constant experience of moderately high positive affect, interspersed only briefly by either higher or lower values, the experience of negative affect proved to be much more volatile throughout the project.

In order to answer our research question, we related different project phases to the recurrence plot. For instance, the holiday period was easily distinguishable from the actual project phases in being much less dense, in both positive and negative affect. Moreover, the actual sprints (i.e., the software development phases) appeared much more homogenous in affective experiences than the review and retrospection phases. Less frequently occurring behaviours (especially high negative affect and low positive affect), in turn, were mainly exhibited in the first weeks of the respective review and retrospection phases. In line with frameworks such as Marks, Mathieu, and Zaccaro (2001) recurring phase model, teamwork can be divided up into action and transition phases. While action phases "are periods of time when teams are engaged in acts that contribute directly to goal accomplishment (i.e., task work)", transition phases can be defined as "periods of time when teams focus primarily on evaluation and/or planning activities to guide their accomplishment of a team goal or objective" (Marks et al., 2001, p. 360). In our application example, action phases are constituted by sprints, i.e., programming and information exchange directed at programming activities, while the transition phases included the evaluation of past activities and planning of future sprints (i.e., are represented by the review and retrospection phases) . This may explain the heterogeneity of affect in the transition phases, as the activities themselves were subject to much greater variation (and uncertainty) than the actual programming, where the objectives had already been defined.

Application example 2: dyadic trajectories

Motivation and research question

One approach to characterize human interaction is in terms of reciprocal behaviour (Chartrand & Bargh, 1999; Dijksterhuis & Bargh, 2001). With regards to verbal interactions, the interactive alignment approach (e.g., Fusaroli & Tylén, 2016) describes the imitation-like coordination of linguistic behaviours between interlocutors, leading to shared linguistic structures and ultimately shared conceptual representations (Branigan, Pickering, & Cleland, 2000; Brennan & Hanna, 2009; Pickering & Garrod, 2013). In appraisal interviews, reciprocal linguistic alignment has been linked to supervisor's empathic communication style (Meinecke & Kauffeld, 2019), which constitutes a critical element of successful leader-follower interactions (Clark, Robertson, & Young, 2018). A potential explanation for this link is that linguistic alignment is related to increased likeability (Meinecke & Kauffeld, 2019). In line with the similarity–attraction paradigm (Byrne, 1971), behavioural alignment induces perceptions of similarity, thereby increasing interpersonal liking and affiliation in interactions (Chartrand & Bargh, 1999; Lakin, Jefferis, Cheng, & Chartrand, 2003). This effect, in turn, is presumed to arise from the positive affective response to behaviourally entraining (i.e., synchronizing one's behavioural patterns over time) with another individual (e.g., Kelly & Barsade, 2001).

The motivation behind the following application example was to analyse the evolvement and effects of linguistic alignment between subordinates and supervisors in the context of an appraisal interview. Assuming that the success of an interview depends on positive responses elicited by behavioural alignment, we concentrate on the co-evolution of the subordinate's and supervisor's verbalizations with regards to their affective valence.

Participants and procedure

For our second exemplar application, we turned to an existing data set comprised by real-time audio recordings from annual appraisal interviews between supervisors and their subordinates (for a previous publication from this data set, see Meinecke et al., 2017). These recordings were gathered in a large production company, had an average duration of about 47 minutes (SD = 18.60), and focused on the subordinate's performance during the previous years as well as his/her future development within the company. As an exemplary illustration, we selected one dyad in which the subordinate rated the appraisal interview as particularly successful (and as particularly unsuccessful, respectively). Perceived interview success was measured using an adapted 6-item scale developed by Kauffeld, Brennecke, and Strack (2009). A sample item was "I enjoyed the appraisal interview very much" (α = .94). Participants indicated their responses on a scale from 1 (*not at all*) to 6 (*very much*).

Data formatting

Leader-follower interaction processes were assessed based on verbatim transcriptions of the communications among both interview partners. Specifically, each discrete word in the flow of dyadic conversation was classified using the Linguistic Inquiry and Word Count (LIWC), which is a computerized dictionary-based text analysis programme (Pennebaker, Francis, & Booth, 2001). As our study was conducted in German, we employed the German version of the LIWC dictionary (Wolf et al., 2008). In our analysis, we focused on the supervisor's and subordinate's use of affect words, including displays of both positive (e.g., happy, proud) and negative (e.g., scared, angry) affect.

Analyses were performed on the speaker-turn level, i.e., one unit in our time-series data was equal to one speaker turn. The successful interview comprised a total of 73 speaking turns and the unsuccessful interview 71. We used categorical CRQA as the affect displayed during each speaker turn was coded as either positive, negative, both, or absent. That is, when words laden only with positive affect were present during a speaker turn, a value of 1 was assigned. If only negatively laden words

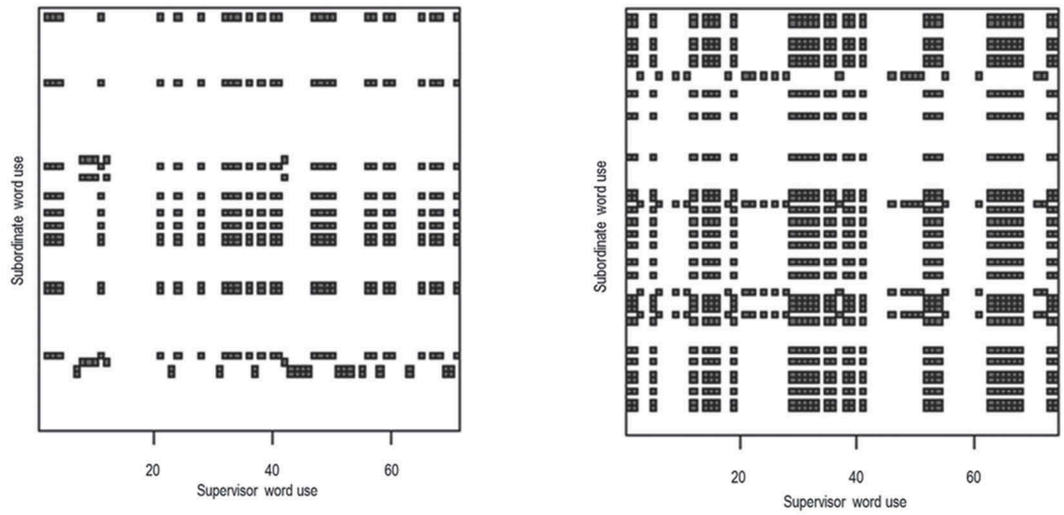

Figure 4. Cross-recurrence plots representing verbal alignment between supervisors and their subordinates across two appraisal interviews (application example 2). Each time unit corresponds to a turn of talk. The left plot shows the results for the interview perceived as unsuccessful by the subordinate, the right plot shows the data for the successful interview. Shaded black areas denote recurrence, indicating that the same affect words are being present in the supervisor's and the subordinate's following speaking turn.

occurred, this resulted in a value of two, if both positive and negative affect words were present, this turn received a value of 3. Absence of any type of affect was initially categorized as 0. However, as we were interested only in affect occurrence, not absence, all zeros were subsequently transformed to unique numbers in order to avoid recurrence detection.

To visualize the cross-recurrence for both dyads and to extract the respective quantitative measures in the observed appraisal interviews, cross-recurrence plots were generated with the crqa library in R (Coco & Dale, 2014). We chose the simplest combination of parameters sufficient for categorical CRQA (e.g., Dale, Warlaumont, & Richardson, 2011; Main, Paxton, & Dale, 2016), using a single embedding dimension, a default lag of 1, and a radius of 0. Accordingly, we examined turn-by-turn instances of affective expressions that matched precisely between the subordinate and supervisor.

The cross-recurrence plot (see Figure 4) enables the extraction of information on the dyad's interactive affective alignment. The diagonal line in the cross-recurrence plot signifies the perfect alignment between two time series. The *x*-axis shows the time series for the supervisor and the *y*-axis shows the time series for the subordinate. In our data, consecutive speaking turns are treated as parallel instances. More specifically, as the supervisor generally began the appraisal interviews, the subordinate's subsequent speaking turn was regarded as a parallel instance. Accordingly, in our data, a perfect alignment was equal to the same affect words being present in the supervisor's and the subordinate's following speaking turn. If one person's affect lagged more than one speaking turn behind the other's, the cross-recurrence plot would show clusters of points shifted off-centre.

Data analysis and discussion

While the appraisal interview perceived as successful exhibited a recurrence rate of 16.5%, the one perceived as unsuccessful obtained only 6.6%. This numerical difference was supported by the visual contrast between the two cross-recurrence plots: Whereas the successful interview exhibited larger "chunks" of recurrence, the unsuccessful interview was characterized by comparatively small and scattered clusters of recurrent events (see Figure 4). As evident from the white area above the *x*-axis (i.e., the bottom rows exhibiting no recurrence points), the supervisor's affective expression was not reflected in the subordinate's behaviour until many turns later. In contrast, while it also appeared to have taken some time in the successful interview, here the behavioural recurrence was visible much earlier.

Looking not only at the length of the "recurrence blocks" (i.e., the number of black dots aligned on top of one another), which signify the recurrence on the subordinate's part, the width of these blocks demonstrate that the supervisor consecutively revisited the same affective state. Looking into the nature of the repeatedly displayed affective states, these were mostly positive, for both supervisor and subordinate. In comparison, the unsuccessful interview showed not only less recurrence on the subordinate's but also on the supervisor's part. Here, while the subordinate's repeated affective expressions (which generally were not many) were also largely positive, the supervisor showed a similar amount of immediate repetitions of positive as well as mixed affect.

Interestingly, both interviews showed the largest clusters of recurrence around the first third to first half of all speaking turns. Looking at the transcripts, this was generally a section where the supervisor gave both positive examples of the subordinate's behaviour and asked the subordinate for his opinion on these – this explains the high degree of recurrence, which pertained mainly to positive affect. Another similarity is the comparatively high degree of recurrence at the beginning of the two interviews. Once again, this can be explained by an alignment of positive affect, beginning with the supervisor thanking the subordinate for his time – statements which where laden with positive affect that were potentially picked up by the subordinate some time later.

Generally speaking, recurrence indicates the extent to which a system revisits previous states. Cross-recurrence, in turn, describes the extent to which one system visits the same states as another. In this application example, this translates into the extent to which the subordinate and the supervisor exhibit synchrony of affective valence in their respective speaking turns, that is, the extent to which they align with another regarding affectively laden verbalizations. Looking at the results, several conclusions can be drawn in order to address our research question. Firstly, a high degree of cross-recurrence suggests that interlocutors are able to verbally entrain with one another, striving towards perfect alignment. Accordingly, the interview which was perceived as more successful showed a higher degree of behavioural recurrence compared to the one perceived as less successful, supporting the interactive alignment approach. It seems likely that by verbally aligning with the subordinate, the supervisor was perceived as more similar, likeable and empathetic (cf. Meinecke & Kauffeld, 2019), thus fostering an overall more successful interaction. Secondly, the results from the recurrence plot showed that in the successful interview subordinate and supervisors behaviours occurred in rapid succession – as opposed to the less successful interview, where matching behaviours were interrupted by much longer intervals. While the former suggests that the interlocutors directly picked up each other's behaviour – signifying well-functioning entrainment – the latter implies that matching behaviours may not have been directly related to one another, given the long delay. Hence, behavioural alignment can also be understood as smoothly functioning coordination, leading to perceptions of more pleasant and satisfactory interactions (e.g., Fusaroli & Tylén, 2016; Kelly & Barsade, 2001). Finally, behavioural entrainment is assumed to elicit positive affective reactions in both interaction partners, thus promoting affective convergence (Kelly & Barsade, 2001). In our application example, the perceived similarity in verbal expressions of affect was thus likely to trigger positive sentiments, leading the interlocutors to converge in positive affect, thereby ultimately promoting further positive expressions. This theorizing may be supported by the higher extent of positive affect expressed in the successful interview.

Application example 3: team trajectories

Motivation and research question

An alternative approach to interactive alignment is that of interpersonal synergies (Fusaroli & Tylén, 2016). While interactive alignment asserts that structural organization is reflected in interlocutors' linguistic synchronization, the interpersonal synergy approach assumes that interlocutors complement each other in jointly evolved interactional routines. That is, instead of distinguishing between interlocutors' respective speaking turns, interaction is treated as coherent and co-constructed by multiple interlocutors. This concept reflects that in order for interacting individuals to engage in joint action, they must complement each other's behaviour, rather than mirror it. For instance, a question should not necessarily be followed by an (identical) question, but rather by the corresponding answer (Enfield, 2013; Goodwin & Heritage, 1990). Consequently, interpersonal synergy can be described as a complex process through which interlocutors become interdependent in their intricate conversation dynamics, adapting and complementing each other, thereby developing patterns of stable interactions (e.g., Dale, Fusaroli, Duran, & Richardson, 2013; Fusaroli & Tylén, 2016).

Team processes are defined as mechanisms where "team members combine their individual resources, coordinating knowledge, skill, and effort to resolve task demands" (Kozlowski & Ilgen, 2006, p. 81). Central to this conceptualization is the interdependence of team members' acts, which are jointly directed towards task execution (e.g., Kozlowski & Ilgen, 2006; Marks et al., 2001). Interpersonal synergy is defined by interdependence and complementarity through which individuals' interactions are transformed into interpersonal interaction systems. On this basis, it appears to be a promising approach to study interaction processes involving multiple individuals targeted at joint task execution (e.g., work teams). Accordingly, the third and last application example will concentrate on a team meeting of highly skilled researchers, developing innovative research ideas. We assume that in order to reach high meeting satisfaction and function effectively (i.e., jointly generating and discussing ideas and implementation strategies), we should be able to observe stable interaction patterns reflecting the complementarity of team members' contributions unfolding over time.

Participants and procedure

Our final application example is based on a recent data set comprised by a total of 68 video recordings of organizational team meetings comprising a total of 448 participants. Participants were researchers, mostly from technical (50%) or life science (22%) disciplines. Participants' mean age was 30.3 years (SD = 5.9 years). From this pool we selected two teams on the basis of their satisfaction with their meeting. Meeting satisfaction was assessed using an adapted version (4 Items) by Kauffeld and Lehmann-Willenbrock (2012). Sample items were "I am very satisfied with this meeting's progress" and "I am very satisfied with this meeting's results" (α = .84). Items were answered on a scale from 1 (*strongly disagree*) to 5 (*strongly agree*). Over all teams, average meeting satisfaction was 4.16 (SD = 0.36), and we selected the team with the lowest (3.25) and highest (4.89) meeting satisfaction values for our application example. The meeting with the lowest satisfaction comprised three, the team with the highest satisfaction four team members.

Data formatting

We coded the observed team meeting interaction using the act4teams coding scheme (e.g., Kauffeld & Lehmann-Willenbrock, 2012; Kauffeld, Lehmann-Willenbrock, & Meinecke, 2018). All interaction units were directly cut from the video stream using INTERACT software (Mangold, 2014). The unit of analysis was in form of communicative thought units which can be described as the equivalent to a single simple sentence (Bales, 1950). Our two sample meetings held 548 (i.e., the high satisfaction team) and 775 (i.e., the low satisfaction team) interaction units, respectively. Subsequently, each unit was assigned to one of the 43 fine-grained codes of the act4teams coding scheme, which enables a detailed representation of interactions within a meeting. Act4teams is an exhaustive and mutually exclusive coding scheme, i.e., all statements are assigned to a behavioural category and any particular statement will match only one category. The 43 fine-grained codes, in turn, are assigned to higher-level macro categories, namely problem-focused, procedural, relational (i.e., socio-emotional), and action-oriented communication. Further, the last three macro categories can be divided into both functional, as well as dysfunctional or counterproductive facets. For instance, while *procedural suggestion* and *summarizing* would be examples of functional procedural communication, *losing one's train of thought* would be a dysfunctional example. Statements that could not be assigned to one of the 43 categories of the act4teams coding scheme were coded as "other behaviour" (e.g., incomplete statements, laughter). For examples of verbal statements coded with act4teams, see Meinecke and Lehmann-Willenbrock (2015).

In our application study, all counterproductive statements were subsumed under one category, while the functional statements were assigned to their respective categories. Accordingly, we arrived at a total of five categories: problem-focused, procedural, relational, action-oriented, and counterproductive statements. Finally, with each communicative thought unit, we also coded who the speaker was.

Again, we applied RQA using the software package nonlinearTseries in R to visualize the recurrence plots for both teams and to extract the respective quantitative recurrence measures. To calculate the recurrence in this particular data set, we computed a variable which had n (number of members per team) x k (number of codes) levels, i.e., one level for every different behaviour shown by each team member. For instance, in a team of four members, using the above-mentioned coding scheme comprising five different codes, we would arrive at 20 different possibilities for coding this event. Subsequently, we assigned a number to each of these different levels, e.g., all problem-focused statements raised by team member A were represented by the number 1. The same codes voiced by the same team members were thus represented by the same numbers, with the exception of behaviours that could not be coded (e.g., due to unintelligible statements), which were assigned to unique numbers. The latter implies that these were behaviours that did not repeat themselves and should thus not be reflected in any type of recurrence.

Data analysis and discussion

The teams in our application example showed a recurrence rate of 20.7% (low satisfaction) and 14.5% (high satisfaction), respectively. While Figure 5 shows standard black and white recurrence plots (cf. application example 1), Figure 6 shows colour-coded plots (different colours = different codes; different shades = different speaker/team members) to further facilitate reading and interpretation.

At first sight, we found support for the differing recurrence rates: As opposed to the high satisfaction team, the low satisfaction team's plot appeared much denser, signifying more recurrence. The inspection of the colour-coded data also enabled us to understand the quality of this recurrence. While the plot of the low satisfaction team was particularly dense with regards to problem-focused behaviours (blue), the high satisfaction team exhibited a constant intermittence of problem-focused by socio-emotional (red) behaviours. Moreover, whereas the low satisfaction team showed constant recurrences of problem-focused behaviours throughout the entire meeting, the high satisfaction team showed a behavioural change approximately at the meeting's midpoint. The first phase, which persisted for roughly the first 200 behavioural units, appeared less dense and somewhat "messier" in the black and white plot. The colour-coded plot, in turn, revealed different shades of blue (problem-focused communication), interspersed with red (socio-emotional communication) and green (procedural communication) elements. Accordingly, the lower recurrence in this phase can be explained by different communicative foci (i.e., problem-focused, socio-emotional, and procedural statements).

Looking at the individual codes, this manifested itself in initial discussions on the meeting's agenda and task priorities (procedural communication, e.g., procedural questions), followed by the team members pooling the information they had on their task (problem-focused communication, e.g., sharing organizational knowledge, identifying problems) and verifying whether they were on the same page (relational communication, e.g., providing support, giving feedback). However, as evident from the different shades of blue, the low density (or "messiness") of this initial meeting phase was also characterized by an alteration in speakers, particularly regarding the exchange of information.

This phase was followed by an intermediary period which lasted for approximately 100 units. Inspection of the colour-coded plot enabled to distinguish this phase by the high extent of socio-emotional behaviours (red), this time interspersed with occasional problem-focused behaviours (blue). The rest of the meeting was characterized by a large "chunk" of recurrence, which was based on problem-focused statements, largely uttered by the same team member (as evident from the dark blue colouring). Interestingly, as opposed to the low satisfaction team, which exhibited highly recurrent problem-focused behaviours until the very end of the meeting, the high satisfaction team did not terminate the meeting with a problem-focus. Instead, we observed a final period of low density, which was characterized by socio-emotional (red), procedural (green), and action-oriented (yellow) communicative elements. Looking into the micro-level interactions behind our colour-coding scheme, this can be explained by the team members praising one another for the good ideas exchanged during the meeting (socio-emotional), action-planning statements pertaining to tasks to be carried out after the meeting (action-oriented), and recording the discussed information for everyone to see (procedural).

Looking at these results, we derive the following conclusion for our research questions: As opposed to the interactive alignment approach, where a high degree of (cross-) recurrence indicates matching and well-coordinated behaviours (cf. Application Example 2), a high degree of recurrence may not necessarily be beneficial from an interpersonal synergies perspective. Given that we coded the same behaviour displayed by the same individual as being identical, a high degree of recurrence in our example implied that team members rarely alternated or changed their behaviour. These assumptions are substantiated by the qualitative results obtained in the colour-coded plots. Here, the low satisfaction team showed very dense behavioural "chunks", signifying a low degree in alterations of speakers and different types of

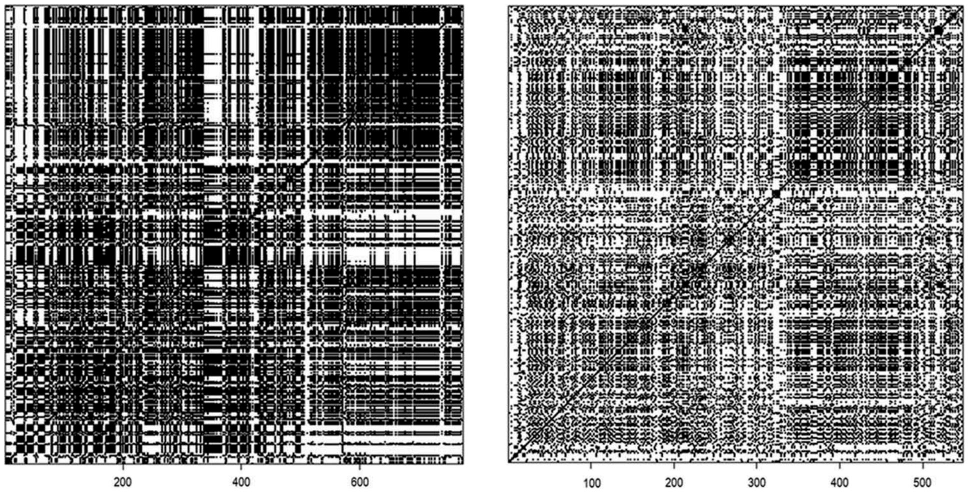

Figure 5. Recurrence plots for two teams (application example 3). On the left is the plot of a team that reported low meeting satisfaction, on the right is the plot of a team with a high meeting satisfaction.

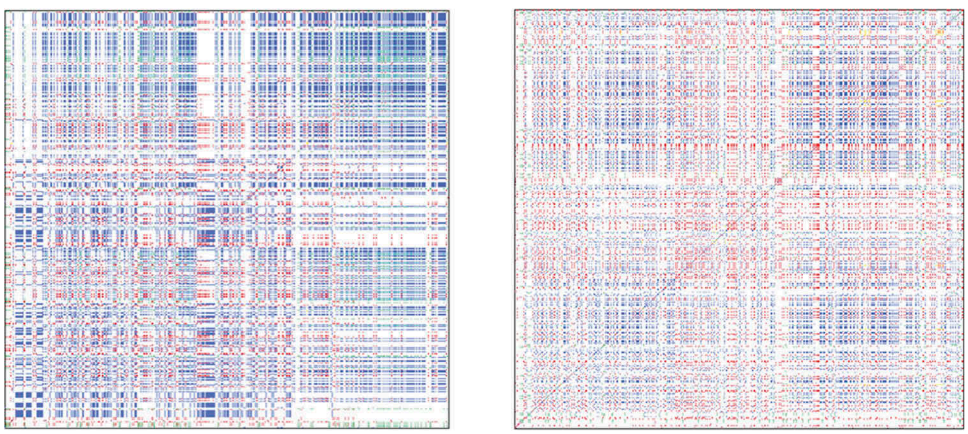

Figure 6. Colour-coded recurrence plots for two teams (application example 3). On the left is the plot of a team that reported low meeting satisfaction, on the right is the plot of a team with a high meeting satisfaction.

contributions. The "messier" phases in the high satisfaction team's plot, in turn, could be attributed to team members alternating speaking turns. Accordingly, a high degree of recurrence may suggest a low extent of complementarity within the interpersonal action system, i.e., the meeting. That is, dense recurrence plots may reveal the team's difficulty in adapting to one another and developing complementarity actions towards joint task execution.

However, this may not necessarily inversely imply that very low/no recurrence should be seen as the ultimate goal. No recurrence infers completely random behaviours, suggesting that team members exhibit chaotic, uncoordinated behaviours, ultimately acting independently (rather than interdependently) from one another. Consequently, one could assume that a moderate degree of recurrent behaviours is necessary as a premise for team members to pick up on each other's behavioural patterns and complement these accordingly.

Implications, limitations, and recommendations

There is an increasing consensus among organizational scholars that numerous phenomena in organizations are subject to non-linear change. Yet, empirical research struggles to keep up with a growing theoretical base that focuses specifically on temporality and non-linearity in organizational research. This paper set out to highlight how (C)RQA – a relatively new method in team and organizational research (cf. Knight et al., 2016) – can be used to capture non-linear trajectories in time-series data.

Implications for organizational research

(C)RQA offers several opportunities to innovate the study of process dynamics in organizations and shed new light on the way individuals, dyads, and teams interact with one another and their surrounding environment across time. In the following, we highlight four selected strengths and benefits.

First, (C)RQA offers broad possibilities for visualizing non-linear processes. The recurrence plots provide more intuitive access to detailed, fine-grained time-series data. Process dynamics that might otherwise be perceived as messy or disorganized thus become more accessible to the researcher (e.g., Cronin et al., 2011). For example, if fine-grained interaction data were gathered as in our second and third application example, researchers might be confronted with the problem of having to make sense of the detailed and massive information that they gathered. The “bigger picture” of group interaction might get lost and researchers might wonder how to handle this substantial amount of data. In fact, researchers have recently argued that interaction data poses challenges similar to that of big data derived from, e.g., online discussion boards or Twitter (Klonek, Hay, & Parker, 2018). With the help of (C)RQA, repeated patterns in interactions, rapid changes, or break-points can be identified through visual inspection. Additional colour-coding can aid interpretation. (C)RQA thus allows a fresh look at unfolding process dynamics by disclosing regularities in chaos (Knight et al., 2016). These visualization capabilities of (C)RQA are not only helpful to the researcher, but may also help to communicate research results more effectively (cf. Ertug, Gruber, Nyberg, & Steensma, 2018).

Second, the potential of (C)RQA also points to the clustering of different types of time series. That is, the recurrence plots and subsequent quantifications could be used to identify those individuals, dyads, or teams that show similar growth trajectories, thereby identifying “typical” patterns (see also Herndon & Lewis, 2015). (C)RQA not only allows for a comparison within dynamic systems (such as a team) but also between systems. As such, (C) RQA seems to be an ideal methodological tool to test ideas from dynamics systems theory and explore research questions related to the conceptualizations of individual, dyads, or teams as complex and adaptive systems. Recent theorizing in the team literature takes this thinking even one step further. In their paper on team fluidity, Mortensen and Haas (2018) provoked the idea of reconceptualizing teams in terms of dynamic hubs of participation instead of bounded team membership. Team membership would then be less defined by formal criteria but rather by shared interaction patterns. Such ideas challenge what we know about how teams work together and also how we conduct team research – especially in the field. When clear team affiliation fades or becomes obsolete, boundaries between teams become increasingly blurry. Interaction structures likely become more flexible and emergent team states become more fragile (Mortensen & Haas, 2018). (C)RQA could provide one way to test difference and similarities between rather traditional work groups and those teams that are increasingly characterized by fluid and multiple team membership. For larger samples, the many and varied measures might be especially helpful in determining relationships across different dynamic systems.

Zooming in on the versatility of (C)RQA, two additional methodological benefits become apparent. From a conceptual perspective, (C)RQA can be applied to any type of dynamic system whether that is an individual, a dyad (e.g., Angus et al., 2012), a team (e.g., Gorman et al., 2012), or even a larger system such as a department or even an entire organization (for further real-world applications see Marwan, Riley, Guiliani, & Webber, 2014). Pivotal here is that the respective research question focuses on change processes and not on static snapshots. Which data is used is then flexible, as long as it is time-series data with a higher sampling rate. As a cautionary note, (C)RQA itself – as a methodological tool – cannot sufficiently specify appropriate time windows and sampling rates. A close connection with theoretical considerations is therefore important to obtain recurrence plots that not only look pretty, but also reflect a meaningful time period and appropriate level of granularity.

Focusing on social interaction processes, (C)RQA can be used to analyse functional communication patterns as in our third application example (see also Gorman et al., 2012), alignment in word use as in our second application example (see also Fusaroli & Tylén, 2016), or within-person trajectories of affective, cognitive, or motivational states as in our first application example. In addition, RQA and extensions of the methods have also been used to explore motor and physiological coordination (Mønster et al., 2016; Strang et al., 2014), eye movement patterns (Anderson, Bischof, Laidlaw, Risko, & Kingstone, 2013; Richardson & Dale, 2005), or alignment in lexicon and syntax (Orsucci et al., 2006). Finally, initial attempts are made to apply RQA to larger systems. For example, there are first applications in the field of economics with RQA studies shedding light on financial time series (Strozzi, Zaldívar, & Zbilut, 2007) as well as business and growth cycles (Crowley, 2008).

These examples lead us to our final point: (C)RQA can be applied to both categorical and continuous data. Examples for categorical data can include coded communication data, either derived from face-to-face interactions or from written communication (e.g., email exchange). Categorical time-series data can be further extracted from coded texts (e.g., documents), calendar entries, or from rather traditional survey approaches as in our first application example. Looking at continuously sampled signals, possibilities seem even larger. Especially the combination of CRQA with physiological data such as heart rate, skin conductance, or facial electromyography monitors is promising (e.g., Mønster et al., 2016; Wallot, Mitkidis, McGraw, & Roepstorff, 2016), be it for specific questions relating to synchrony in leader-follower interaction, or more generally to stress/health, and affect in organizations. In sum, a combination of different streams of time-series data could help to flesh out a more wholesome analysis of temporally sensitive organizational phenomena.

Limits of the method and recommendations

Despite the many opportunities offered by (C)RQA, the methodology has some limitations, which we want discuss next. First, there are limited recommendations and existing rules of thumbs concerning sampling strategies and the granularity of categorical data needed to obtain a recurrence plot with not too much or too little recurrence. In general, (C)RQA is a model-free analysis technique, meaning that no model is fit to the data. As a result, (C)RQA makes no assumptions about the underlying distribution of the data, and is extremely robust against outliers (see Marwan et al., 2007, for a detailed description of the underlying mathematics). With regard to the number of data points necessary to conduct the analysis, the bare minimum from a technical point of view are three data points. However, this is usually not sufficient of any real-world data case and limits the robustness of the results.

We would suggest that the actual amount of data points needed should be dependent on two factors: First, the longest time scale on which the event in question (e.g., an episode of teamwork) unfolds, and second the adequate sampling rate that is necessary to capture the relevant dynamics that unfold within that time scale. Obviously, those two factors do vary with the phenomenon in question, as well as with the measure of choice.

A second limitation concerns that even though (C)RQA provides numerous measures that can be derived from the plotted time series, identification of non-linear patterns and their interpretation largely depends on the researcher (cf. Ramos-Villagrasa et al., 2012). Results of (C)RQA gain most relevance within a precise theoretical context. This underscores that it is the researcher's task to process the manifold information and interpret them in light of the respective study, research question, and design of the recurrence plot. The interpretation of the quantifications is made more difficult by the fact that there are no clear guidelines for organizational research yet, that can serve as a guide in interpretation (e.g., when looking at communication, what characterizes high, moderate, or small determinism?). As such, we would recommend not to get lost in the quantifications but to always couple the measures with the actual visualizations of the respective recurrence plots. It can be very helpful to additionally colour-code the plots as this can further aid interpretation.

On the other hand, focusing too much on the recurrence plots could also lead to the researcher suddenly feeling like an art historian analysing a painting. Especially process data gathered from real social interactions is never as rhythmic and clearly defined as the song example shown in Figures 1 and 2. Interpretation may therefore be guided by additional questions to keep focus, e.g., where is the team currently in its development? What tasks does the team have to accomplish? How is the team composed (e.g., self-managing team)? In order to structure the interpretation of the recurrence plot, it may be helpful to divide the recurrence plot into temporal phases (see Figure 3). Likewise, it may be helpful to first focus on the main diagonal and to assess instances of recurrence that are more closely related in time (i.e., stronger immediate temporal dependency). Then, gradually, the gaze could wander in wider circles and instances of recurrence could be considered that are farther apart. In our opinion, it is a strength of (C)RQA that the method is rather descriptive in nature as this allows a new view on how processes evolve over time. Thus, the qualitative "reading" of the recurrence plots, albeit somewhat unusual, can help to shed new light on process dynamics.

Third, while conducting our own research, we discovered that scaling greatly changed the appearance of the recurrence plots. In particular, our final application study way based on a large number of coded events for each plot (i.e., several hundred coded events per team meeting). This resulted in very dense recurrence plots. Zooming in and out of the recurrence plots changes the "readability" of the plots and the interpretations that can be derived from them. As there are no clear guidelines to follow, the versatility and possibilities of the method can be overwhelming to the researcher. Thus, there is a trade-off between detailed descriptive research and generalizability and a risk of over-interpretation. Extensive time-series data with several hundred measurement points will likely always be characterized by a certain degree of chaos and fluctuations (see also Ramos-Villagrasa et al., 2012). Thus, not all break-points in trajectories are likely to be meaningful. In our team application example, we found it very helpful to go back to the actual recordings to see what caused an apparent change in the recurrence plots. So going back to the original data, although time consuming, can help to better understand changes in the visualizations.

In closing, we acknowledge that we focused on an accessible presentation of the method, rather than on its detailed mathematical underpinnings. There is much more to explore about (C) RQA, especially with continuously sampled data such as setting a threshold for detecting recurrence and choosing appropriate embedding parameters (Marwan, 2011). We hope this paper will spark some interest among organizational psychologists and OB researchers more broadly, possibly leading to a more detailed discussion about both the mathematical foundations of (C)RQA and its conceptual value to organizational research.

Conclusion

The process dynamics that are at the core of many organizational phenomena are inherently non-linear in nature. Instead of viewing these non-linear dependencies and diverse growth trajectories as complications for the analysis of process data, we believe that they carry a wealth of important information about the way individuals, dyads, and teams evolve and change over time. To make sense of and quantify such process dynamics, this article focused on (C) RQA, a methodological approach rooted in the dynamic systems literature. (C)RQA discloses the recurrent properties of time-series process data as graphical visualizations (i.e., recurrence plots) and provides a wide range of measures that can be derived from the plotted data. In summary, (C)RQA can provide novel insights into the non-linear dynamics of organizational phenomena. It is a promising method to complement more traditional approaches and a viable addition to the I/O researcher's toolkit.

Notes

1. Readers who enjoyed this particular example may be interested in the web application *SongSim* by Collin Morris which deals specifically with recurrence in song lyrics and poetry: https://colinmorris.github.io/SongSim/#/.
2. We employed R_{CN} as opposed to R_C as measures of within-person variability as not all individuals consistently filled out the weekly questionnaires (i.e., we had differing number of missing values across individuals and not all individuals filled out the questionnaire on a Friday).

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Data availability statement

The accompanying R code and a subset of data is available via the Open Science Framework https://osf.io/xe8hw/?view_only=27cd218b5f0d4a419b5c347cdfd8cfd0

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