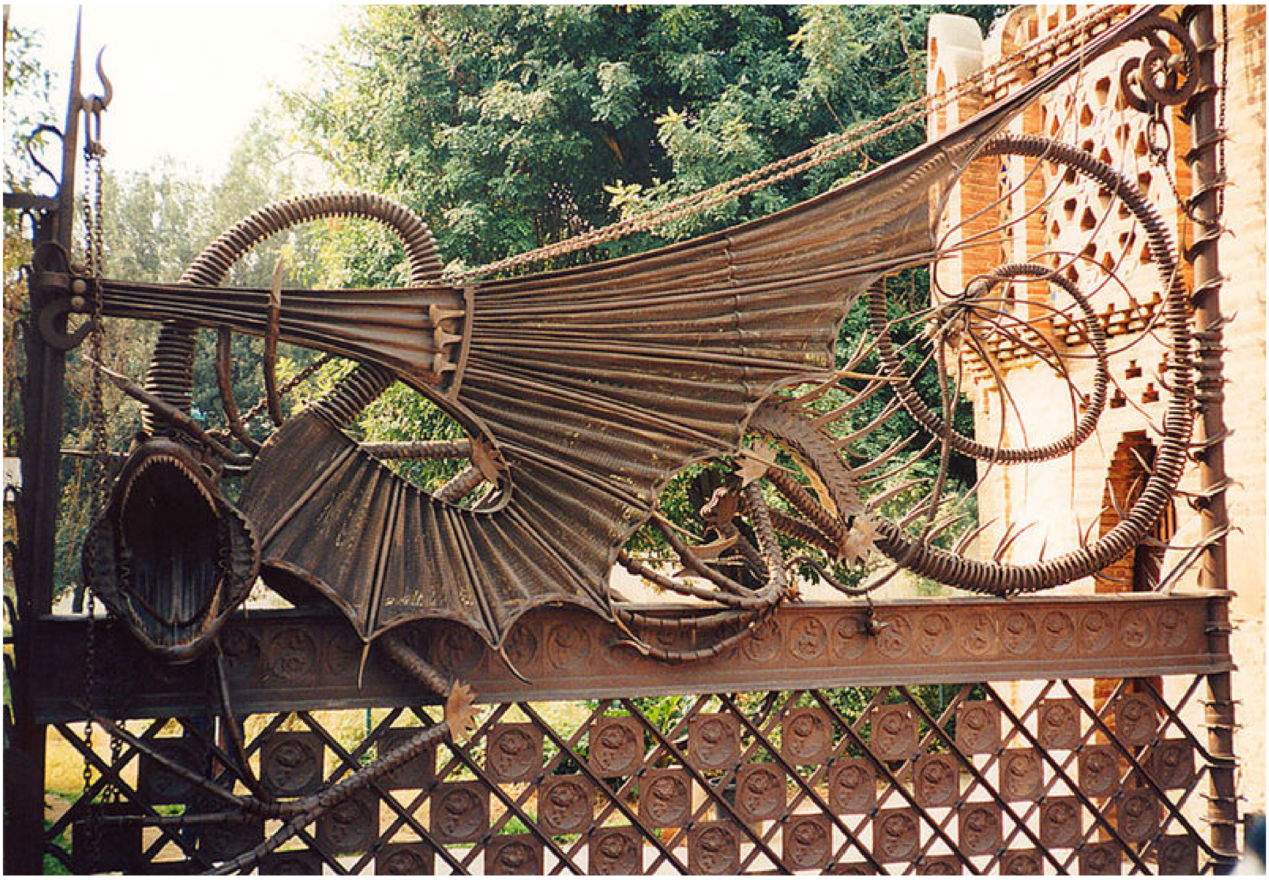
Non-linear Dynamics in Work and Organizational Psychology: To Non-linear Modelling … and Beyond

17th – 18th October 2016
University of Barcelona, Barcelona, Spain

Organizers:

Dr. José Navarro (University of Barcelona), Dra. Rita Rueff-Lopes (ESADE Business School-University of Ramon Llull), Dr. Antonio L. García-Izquierdo (University of Oviedo) and Dr. Jorge Escartín (University of Barcelona)



European Association of Work and Organizational Psychology

UNIVERSITAT DE BARCELONA

psicosao grup de recerca en psicologia social, ambiental i organitzacional

MINISTERIO DE ECONOMÍA Y COMPETITIVIDAD

EAWOP Small Group Meeting *on* Non-linear Dynamics in Work and Organizational Psychology: To Non-linear Modelling … and Beyond

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With the sposorship of:

EAWOP - European Association of Work and Organizational Psychology (www.eawop.org)

UB - Universitat de Barcelona (www.ub.edu)

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Non-linear: *adj.* Not denoting, involving, or arranged in a straight line
math. Designating or involving an equation whose terms are not of the first degree.
phsy. Involving a lack of linearity between two related qualities such as input and output.

Dynamic: *adj.* (of a process or system) Characterized by constant change, activity, or progress.
phsy. Relating to forces producing motion.

Oxford Dictionary

Conference information

Scope and Objectives

The main objective of this meeting is to foster debate and knowledge sharing among scholars interested in going beyond the generalized linear modelling. Very often we find, as part of the limitation of empirical researches, statements describing that data could have been also analysed taking advantage of nonlinear methods. However, the application of non-linear models in our field is not as common as it could be.

Being true that the majority of the accumulated research in the field uses classical statistical techniques based on the generalized linear model (GLM), it is also true that the nonlinear models tend to present better fit indexes and to explain more variance in comparison to the linear ones. For example, in a review about the topic, Guastello (2002) reports that nonlinear models explain the double of variance of their linear counterparts. Nevertheless, the predominant research continues to use linear modelling. Consequently, an important avenue to improve and advance knowledge is related to the use of best suited models. This potential has been emphasized in recent handbooks (e.g., Deboek, 2012; DeShon, 2012; Guastello, 2013; Ployhart & Kim, 2013), specialized books (e.g., Scarborough & Somers, 2006) and recent advanced training institutes (e.g., Nonlinear Method for Psychological Science at University of Cincinnati, June 15-19, 2015, promoted by APA). We aim to add to these important contributions with a Small Group Meeting exclusively focused on nonlinear methods applied to organizational research.

In this meeting we make a call for work and organizational psychologists who are applying different kinds of nonlinear modelling, in any kind of work and organizational psychology topic, including but not limiting to:

- Classic exploration of quadratic and cubic relations among variables (using nonlinear regression techniques, for example).
- The exploration of sigma-functions (another kind of cubic relations) by means of neural networks, functional data analysis, or similar procedures.
- More sophisticated techniques such as catastrophe modelling (which allow to model linear and nonlinear relations at the same time) and fuzzy logic to model any relations that we can imagine by using fuzzy patches.

We extend this invitation to others scholars that, although may not be applying these models in the present, are curious in deepening their knowledge on this type of methods. We believe that the eclectic dissemination of nonlinear dynamics will be more effective in terms of raising general awareness and interest.

We expect this meeting would provide useful guidelines about how different nonlinear models can be applied in the field of work and organizational psychology. To ensure this, and in addition to the presentation and debate of the different contributions from the attendants, we have included a workshop about how to work using nonlinear models.

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Conference venue & Venue map

The small group meeting will take place at the Faculty of Pscyhology of the University of Barcelona. We will be at room 12 in the Palau de les Heures. On both meeting days, members from the organizing committee will guide you to the meeting room. You can get a map about how to arrive to the Faculty here:

www.ub.edu/psicologia/en/coneixer-la-facultat/ubicacio-i-acces

Registration

Registrations will also take place at the same meeting room. You can register on Monday 17th of October, from 8:15 to 8:45 or on both conference days. We will provide you the conference material (a print copy of this documment) and the tiquets for lunches.

WiFi

Free wireless connection will be available during the meeting. You will receive information about how to use it upon registration.

Coffe-breaks and lunches

On both conference days we will have two coffee-breaks (at 11:00 and 16:30 hours) and will provide a lunch in the campus restaurant. Tiquets for these lunches will be gived in the registration.

Information for presenters

The plan is to have 30 minutes per each presentaion. Considering this, we suggest to use 15-20 minute for the presenter leaving the rest (10-15 minutes) for questions and discussions. Due the format of the small meeting in which all the participants are attending the same events we would like to encourage extensive debates in each of the presentations.

Social events: Informal dinner reception

For those arriving on the 16th (Sunday) an informal welcome reception will be held in Barcelona. Please, contact with Rita Rueff-Lopes (rita.rueff.lopes@gmail.com) for details.

Program outline

Monday, 17th		Tuesday, 18th	
8:45- 9:00	Welcoming session Plan overview	9:00 – 11:00	Oral communications III A. L. García-Izquierdo et al., University of Oviedo S. Pasarakonda et al., ETH Zurich P. Costa et al., Instituto Universitário de Lisboa J. Navarro et al., University of Barcelona
9:00 – 11:00	Nonlinear analysis in W/O Psy. Workshop S. Guastello, Marquette University		
11:00 – 11:30 Coffee break			
11:30 – 13:00	Nonlinear analysis in W/O Psy. Workshop S. Guastello, Marquette University	11:30 – 13:00	Oral communications IV P. Marques-Quinteiro et al., Instituto Superior de Psicologia Aplicada, Lisboa J. Hofmans et al., Vrije Universiteit Brussel T. Rebelo et al., University of Coimbra
13:00 – 14:30 Lunch			
14:30 – 16:30	Oral communications I P. J. Ramos-Villagrasa et al., University of Zaragoza R. Gerlach et al., Technische Universität Chemnitz A. Dal Forno, University of Torino A. Hernández et al., University of Valencia	14:30 – 16:30	Oral communications V D. Balas-Timar et al., University of Arad M. Vraný et al., Charles University in Prague J. Escartin et al., University of Barcelona J. Sosnowska et al., Vrije Universiteit Brussels
16:30 – 17:00 Coffee break			
17:00 – 19:00	Oral communications II C. Marques et al., Instituto Universitário de Lisboa C. Gockel et al., University of Applied Sciences Berlin R. Rueff-Lopes et al., ESADE Business School, Barcelona A. J. Silva et al., Instituto Universitário de Lisboa	17:00 – 18:30	General debate

WORKSHOP

Nonlinear analysis in Work/Organizational Psychology Workshop

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One of the earliest concepts in organizational science is that organizations change and develop over time. This point seems to have been lost in the conventional paradigm of understanding interesting variables and mean differences. If we are to understand an organization as a *complex adaptive system*, however, we suddenly see patterns of variability that we know as nonlinear dynamics. If we study phenomena from the nonlinear perspective, we see that about one-third to one-half of the variance we can account for is actually associated with the temporal patterns themselves. Thus the overall plan for the workshop is to connect organizational concepts and phenomena with nonlinear methods.

The workshop is divided into four basic segments: (1) some phenomena of central interest to the profession, (2) theory of nonlinear statistical analysis, (3) an overview of computer programs that help get the job done, (4) an experiential event, the Chaos Exercise, that conveys what chaos in a work process *feels* like and what it takes to manage it.

Conventional thinking tends to regard personnel selection, training, motivation, performance, and turnover as separate questions and phenomena. Indeed there are many ideas to think about in each area. If we think about them as one integrated nonlinear process, however, the situation actually simplifies even though we use models that are more complex than straight lines to explain the dynamics.

Similarly, conventional thinking regards the impact of cognitive workload and fatigue on performance as separate issues. If we observe people work over time as workload changes, there are dynamics that are pushing performance upward and downward simultaneously. We can untangle the performance dynamics by using two connected models strategically.

We will also discuss group dynamics that involve different nonlinear time series models, notably coordination, adaptability and resilience, leadership emergence, and physiological synchronization. There are many unresolved questions concerning group dynamics, and nonlinear dynamics offers new insights about how the various phenomena fit together.

Nonlinear dynamics are not the only time series statistics that ever existed; linear time series models are well-known and have been co-opted into some contemporary statistical approaches such as multilevel modeling. The key difference, however, is what we do with the dependent (or non-IID) error and how it plays an important role in our ability to extract the intrinsic dynamics in our data. We will consider how to prepare and analyze data using polynomial regression models, nonlinear regression, symbolic dynamics and entropy statistics.

See more information in the Appendix

COMMUNICATIONS

Teams as Complex Adaptive Systems: A Systematic Literature Review

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José Navarro
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Ramón Rico
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Purpose/contribution
Nearly two decades ago, Arrow, McGrath and Berdahl (2000) state that teams are complex adaptive systems (CAS). Despite the general agreement that this approach is one of the most important contributions made to really understand teams, little has changed in the way in which we make research and practice. In other words, we are analyzing different angles of teams but unable to wholly understand the phenomenon. The solution was pointed out also by McGrath (1991) and is approaching to teams from Nonlinear Dynamical Systems (NDS) theory. However, its usage is still scarce. To contribute to fill this gap, the present contribution is directed to make a systematic review of the empirical research on teams from NDS theory, trying to guide scholars and practitioners into CAS and NDS theory in order to help in further developing of the science of teams.

Design/methodology
We have applied three rounds of review to select which papers would be regarded in our study. Regarding the first round, we have restrained our search to papers published between 2000-2016 on scholarly peer review journal included in three online research repositories (EBSCO Host, B-ON, and Web of Science) with the following combination of keywords in the Abstract: “teams” and “complex adaptive systems”, or “teams” and “chaos”, or “teams” and “chaotic”, or “teams” and “nonlinear dynamic systems”, obtaining 439 hits. In the second round of review we discard from our review papers that (a) were not quantitative research, or in which keywords; (b) were acronyms for unrelated topics or concepts; (c) were surnames; and (d) were used with a different meaning of the one we were looking for (e.g., chaos is deterministic versus chaos is randomness or mess). Applying these criteria we kept 113 hits. Finally, in the third round of review we went looking for duplicate cases, hence retaining 70 articles out of the 113 selected in the second round (approximately 39% less).

Results
The review of the selected articles shows three main conclusions: (1) there still much confusion in the use of “chaos” and “complexity” terms. Nevertheless, complex adaptive systems are more frequently regarded adequately; (2) research on teams as CAS is growing, and has escalated since 2010; y (3) the main topic in team research from NDS theory is the relationship between coordination dynamics and performance outcomes.

Limitations
The main limitation of our study is that the scope of the review. Further research should include other databases and unpublished studies.

Implications
Although NDS could help to a better understanding of teams, researchers are still not aware of the opportunities of this approach. The last five years show an upward trend, but more effort is needed to make NDS theory and its mathematical approach accessible to team researchers.

Originality/value
This review shows that considering teams as CAS and using NDS theory, researchers can obtain a more detailed knowledge of how teams really work, which may help to raise the level of sophistication of existing theories and lead to better informed theoretical and practical applications.

Acknowledgments
The first and third author wishes to acknowledge the support given by the Spanish Ministry of Economy and Competitiveness (PSI2013-44854-R project). William James Center for Research, ISPA, Instituto Universitário is financed by FCT (Ref. UID/PSI/04810/2013).

Notes:

A Question of Time: Team Composition Predicts Initial Levels and Change in Psychological Safety

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Purpose/Contribution
Psychological safety describes a trusting and accepting team atmosphere, where team members can ask others for help and are not afraid to speak their minds (Edmondson, 1999). Research shows that psychological safety is mostly associated with positive outcomes like more learning behavior, better innovation processes, and improved team performance (Choo, Linderman, & Schroeder, 2007; Edmondson, 1999; Schaubroeck et al., 2011).
But how does psychological safety build and develop in the first place? It is the combination of team members' different characteristics that substantially affect the structure and functioning of a group (Hoyle & Crawford, 1994). Thus, we focused on team composition in terms of three deep-level characteristics: attitude towards teamwork, the Big Five personality characteristics, and task-specific skills as predictors for initial levels and change in psychological safety.

Design/Methodology
Fifty-six self-managed student teams (with 3-5 members each) completed a research project in five months. Team composition variables were measured at the beginning of the project with questionnaires. Team psychological safety was measured at the beginning, at the midpoint, and at the end with questionnaires. We used growth curve modeling to predict initial levels and change in psychological safety.

Results
Psychological safety decreased over time. Team members' attitude towards teamwork (but not the Big Five) predicted initial levels of psychological safety. Team members' skills predicted change in psychological safety: The higher the team members rated their task-specific skills at the beginning, the more psychological safety decreased over time.

Limitations
Due to our student sample, results should be generalized with caution. More measurement points, especially in the first phase of team work, would map the development of psychological safety more precisely, especially dynamics around the midpoint which is an important turning point in team development (Gersick, 1988).

Implications
First, the focus on the team itself contributes to understanding the dynamics of psychological safety. Second, our study stresses the importance of changeable variables, namely attitude towards teamwork and task-specific skills, rather than traits (e.g., the Big Five) for the development of psychological safety. Thus, we recommend fostering positive attitudes towards teamwork at the beginning as well as enhancing team resources, e.g. by providing a task-specific training and constructive communication training during the project. Further research should focus on trajectories to gain more insight on how psychological safety changes and how change is related to important outcomes like team performance.

Originality/Value

We put the construct of psychological safety and its development front and center in this study. We also provide answers on how psychological safety builds and develops and which antecedents influence how psychological safety unfolds over time. We believe that studying temporal dynamics in psychological safety in teams fits the scope of the SGM. Using multilevel growth modeling is a good start; however, it might not map change in psychological safety adequately. In the SGM, we hope to learn and discuss methodological approaches to analyze our data in greater depth in order to gain more insight about the linear and nonlinear dynamics of psychological safety within and between teams.

References

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Hoyle, R. H., & Crawford, A.M. (1994). Use of individual level data to investigate group phenomena: Issues and strategies. *Small Group Research, 25*, 464-485.
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Notes:

Effort Dynamics in Supervised Work Groups with Envious Subordinates

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Purpose/contribution
For a long time, emotions in the workplace have been a neglected topic in the organizational behavior literature. Among emotions, envy is ubiquitous although socially undesirable. Many incentives schemes in organizations are built around comparison and, indeed, social comparison is an important theme both in human resource practices and organizational economics; yet, the economics literature has surprisingly devoted little attention to envy. Several authors argue that envy is the product of comparisons with a more successful party in which one views oneself as inferior. Taking into account this definition we want to understand the effects of envy in a model of work group when the object of being envied is one of the members' capacity.

Design/methodology
The effort dynamics is formalized in terms of a nonlinear dynamical system. We chose the supervised work group as main unit of our study, assume that individual income is the same, and envy depends on some characteristics of the envied person. Members’ decisions are the result of elaboration processes, where members’ actions are compared to the existing conditions and adapted to pursue goals.

Results
Our analysis suggests that envy have important consequences on the team dynamics. Firstly, a negative emotion such as envy perturbs the equilibrium. Then, the envied subordinate must be able to properly contain envy, since it is impossible to eliminate it without team production reduction. Either when conflict is simply ignored, or when conflict is not effectively dealt to remove it, production drops.

Limitations
As we are considering a model of a complex interaction our approach suffers from the drawbacks of modeling complexity (Batty and Torrens, 2001). In particular, our model well exemplifies Thorngate's (1976) postulate of commensurate complexity, which was expressed by (Weick, 1979, p.35) as the impossibility for a theory of social behavior, to be simultaneously general, accurate and simple.

Implications
Our model allowed us to see how envy must be contained, and to measure the performance drop due to envy. This aspect makes to consider the principle of good enough which found some interesting applications in business preferring conflict management to resolution. As the common incentive scheme leaves little space to conflict management, this approach can help understand how to find proper strategies that can be formalized by a set of rules to be implemented.

Originality/value
The model we propose captures the non linearity of effort dynamics and shows how envy may affect the group dynamics. The graphical analysis we provide keeps the elegance of analysis and makes the results more intuitive. We are convinced that the joint contribution of our approach and both the empirical and conceptual/theoretical approach to conflict management may bring mutual

benefits for the study of conflict in organization. This is a new challenging way to approach conflict management, and a lot of work must be done to converge towards a common ground.

Notes:

The Counterproductive Influence of Too Frequent Interactions Between Team Managers and Team Members: Investigating Curviliar Relationships and the Moderating Role of Team Tenure and Potency on Team Affect.

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Purpose/contribution

Research has shown the importance of the quality of the interactions between formal team leaders (i.e. team managers) and team members (e.g. Boies & Howell, 2006; Cheng & Li, 2012). However, when focusing on interactions between managers and teams, not all is about quality: the frequency of those interactions (FI) may also play an important role. In this regard, some researchers have suggested that when managers interact more frequently with their subordinates, their working relationships should improve, leading to positive outcomes (Napier & Ferris, 1993; Antonakis & Atwater, 2002). On the contrary, other researchers have suggested that when managers interact too frequently with their subordinates, this may be seen by the last ones as an unnecessary close control (i.e. micromanagement) (Howell, et al., 2005) leading to negative consequences (Frost, 2004; Tepper, 2000; Zellars et al., 2002). Considering these studies altogether, we hypothesize that the relationship between FI and important team states such as team affect, is curvilinear. In addition, based on the substitutes for leadership theory (Kerr & Jermier, 1978), which posits that leadership and supervision may be less important (or even counterproductive) depending on certain subordinates' characteristics such as their capabilities (i.e. potency) or work experience (i.e. tenure), we hypothesize that the curvilinear relationship between FI and team affect is moderated by team potency and tenure.

Design/methodology

Hypotheses were tested using panel data collected in a sample of 55 work-teams by means of hierarchical non-lineal regressions. Two separate sets of regressions were run for two dimensions of team affect: positive and negative affect.

Results

After controlling for team size managers' support, and the corresponding dimension of team affect at Time 1, the results showed that, according to our expectations, the relationship between FI (Time 1) and team affect (Time 2) was curvilinear, with an inverted U-shape for team positive affect and U-shape for team negative affect. Also, for team positive affect, the U-shape relationship was moderated by team tenure and potency. As expected, the curve became increasingly convex downward as team tenure increased. However, for team potency, the results were contrary to the expected ones and the curve became increasingly convex downward as team potency decreased. This may be explained because the high levels of self-confidence shown by teams with high potency may diminish the negative influence of other conditions (Gil, et al., 2005), such as perceiving too frequent interactions, whereas for teams with low potency, perceiving too frequent interactions may reinforce their sense of low self-efficacy and diminish positive affect (e.g. Luszczynska, et al., 2005).

Limitations, implications, and originality/value

Even if FI is an important managerial behavior that can easily be varied to get optimum team results, this is the first empirical study on this topic. Despite the fact that we were not able to control for the quality of the interactions and that FI was measure by means of a subjective scale of frequency, our results have important implications when planning the frequency with which managers should interact with their teams, considering team tenure and potency.

Notes:

Team Processs Adaptation: A Consideration of Pertinent Antecedents Exhibiting Curvilinear Relationships Over Time

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Purpose/Contribution
This study aims to analyze the main effect of team adaptability and both team and task shared mental models (SMMs), as well as the interaction effect between adaptability and SMMs on the trajectory of team process adaptation. The topic of team adaptation has gained prominence in recent years. Specifically, researchers have assessed the effect of a number of predictors on team adaptation - such as SMMs and transactive memory systems (e.g., Marques-Quinteiro et al., 2013; Uitdewilligen et al., 2013). However, most of this work has utilized cross-sectional designs and statistical techniques based on linear models.
We argue that the relationships between predictors and the development of team adaptation is more complex than has been suggested by prior studies and in fact, may be curvilinear. In this study, we rely on longitudinal data to analyze the effect of team adaptability and SMMs on team process adaptation over time.

Design/Methodology
We tested our model with a sample of 33 teams (145 individuals) competing in a management simulation over five consecutive time periods. Data was collected through survey questionnaires and was analyzed using random coefficient modelling.

Results
The results show that there is sufficient variance between teams in the linear and the quadratic trajectory of team adaptation development over time (Δ^2LL = 7.99, $p < .01$). Adaptability is not significantly related to team process adaptation over time (y = -0.05, t = -1.07, p = .29); but both dimensions of SMMs are positively and significantly related to the quadratic development of team process adaptation over time (task: y = 0.10, t = 2.73, p = .01; team: y = 0.11, t = 2.06, p = .04). Furthermore, the results showed that the interaction between adaptability and SMMs on the quadratic development of team process adaptation is positive and significant (task: y = 0.14, t = 2.39, p = .02; team: y = 0.22, t = 2.36, p = .02). In particular, there is a delayed effect of high levels of both adaptability and SMMs on team adaptation. Although in the first two performance episodes, team process adaptation is lower in teams thathave high SMMs and adaptability; in the last two episodes, having high SMMs and high adaptability leads to more adaptation.

Limitations
This study is based on a relatively small sample of teams participating in a simulation. Therefore, the results may not be generalizable to “real world” teams.

Implications
Teams need time to adapt the way they work. It is not enough to have teams composed of members with high adaptability. Instead, it appears that teams need to develop a shared understanding about the important aspects of work as well as be adaptable in order to truly adapt.

Originality/Value
This study reveals that the relationship between predictors and team adaptation is not as simple as many theoretical papers and empirical studies have suggested. Likewise, this study utilizes a new approach to measuring team adaptation – the adaptation of team processes.

References
Marques-Quinteiro, P., Curral, L., Passos, A. M., & Lewis, K. (2013). And now what do we do? The role of transactive memory systems and task coordination in action teams. *Group Dynamics: Theory, Research, and Practice*, *17*, 194-206.
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Notes:

How Trajectories of Shared Leadership Relate to Team Performance

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Purpose/Contribution
Shared leadership occurs when leadership influence is distributed among team members, and it can predict team performance (Carson, Tesluk, & Marrone, 2007). We examined how shared leadership develops from the beginning until the end of a team project and how different trajectories of shared leadership – as compared to absolute levels – relate to team performance. We believe it is important to investigate the development of shared leadership because it is – by definition – a dynamic concept. A focus on trajectories provides more insight into how high and low performing teams differ and enables us to better predict team performance.

Design/Methodology
Fifty-six self-managed student research teams completed a research project over the course of five months. Shared leadership was operationalized as network density (Gockel & Werth, 2010) and assessed at the three most important points in a team's life cycle: beginning, midpoint, and end of the project (Gersick, 1988). Team performance was assessed by instructor ratings. We used the intra-team longitudinal approach (Li & Roe, 2012) to analyze the data, grouped trajectories of network density into four patterns (increase, decrease, inverted-u shape, u-shape), and used these patterns as predictor in the analyses.

Results
We ran an ANCOVA with team performance as criterion and shared leadership pattern as predictor. Number of team members and absolute levels of shared leadership at three measurement points were covariates. Teams showed better performance when shared leadership increased during the second half of the project (as compared to decreased), and when shared leadership was high at the midpoint of the project.

Limitations
Due to the nature of the data and the new methodology, three important questions remain open: First, which specific leadership behaviors help to improve team performance? Second, which triggers cause changes in shared leadership? And third, when can a change in shared leadership (i.e., network density in this case) be classified as a change?

Implications
Results show that an increase in shared leadership in the second half of a team project is related to better performance and a decrease to worse performance. Future research needs to replicate this finding with more measurement points and in different kinds of contexts.

Originality/Value
We show the application and value of a bottom-?-up approach to examining team trajectories. Our results indicate that it might be more important for leadership researchers and practitioners to focus on changes instead of absolute levels of shared leadership for a more comprehensive view on how shared leadership affects team performance.

Fit to the Scope of the SGM

Our study fits the scope of the SGM well because we focus on changes within teams as compared to between teams and take into account different kinds of changes: linear and nonlinear ones. We present how a change can predict an important team outcome. In the SGM, we hope to receive feedback on our approach and learn additional methods of analyzing longitudinal data from teams.

References

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Author’s note: We presented parts of this project at EAWOP 2013 in Münster and are currently in the process of writing up this study for publication. Rebecca Gerlach and Christine Gockel use different data from the same sample for another study also submitted to the SGM.,

Notes:

Forecasting the Influence of Customer Related Micro-Events on Employees' Emotional, Attitudinal and Physiological Responses

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Purpose/contribution

The affective events theory (AET) proposes that daily events elicit affective reactions on workers that, over time, influence affective and judgment-driven behaviors. It also suggests that dispositional traits and appraisal tendencies moderate the relation events-affect. This study aimed to: 1) investigate what customer-related events elicit workers affect; 2) test the moderating role of workers' susceptibility for emotional contagion on the relation events-affect; 3) to explore what affective states influence cardiovascular efficiency and turnover intentions.

Design/methodology

We conducted a longitudinal study in an inbound call-center by following 48 workers during 10 working days, gathering 267 events and 1232 affective reactions. We combined diaries, questionnaires and physiological data. Data was analyzed qualitatively and quantitatively, with artificial neural networks (ANN).

Results

We extracted 13 event categories and found support for the moderating role of workers' susceptibility for emotional contagion. Joy and happiness were the most important predictors of cardiovascular efficiency and anger was the most important predictor of turnover intentions. Both ANNs showed satisfactory predictive values (R^2Turnover = .51, $p < .01$; R^2Cardiovascular efficiency = .16, $p < .01$).

Limitations

Physiological and attitudinal measures were not collected simultaneously with the events.

Implications

Understanding the impact of customers' on workers health and attitudes is crucial for organizations to design interventions aimed at reducing this impact.

Originality/value

This study combined different methods, resorting to powerful and robust data analysis tools. It also gathered longitudinal and physiological data. This was the first time that emotional contagion was integrated in the AET.

Notes:

Capturing Moments in the Workplace: A Nonlinear Approach to Study Daily Hassles at Work, Work Engagement and Creativity

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Abstract

Daily hassles are a constant in daily life at work. It is shown that these kind of daily events affect diverse outcomes (e.g. well-being). In this study, we aim explore whether the relationships between daily hassles, mindfulness, work engagement and creativity are linear or nonlinear ones. To achieve that, we conducted a diary study through five working consecutive days within a sample of workers. So far, we have 45 participants (N = 45*5 = 225), however we are still gathering data. This study is intended to use non-linear analyses, once it is proved that nonlinear models should be applied to the study of work and organizational psychology. Moreover, we believe, that this study will provide new theoretical elements for models that explain employees work engagement and creativity at work. Additionally, the use of nonlinear analyses will give insights into the use of these kind of statistical methods within organizational behavior. Thus, results will arise implications for employee health and organizational success.

Keywords: daily hassles, mindfulness, work engagement, creativity, nonlinear modelling.

Notes:

Biodata and Fairness in the Assessment of Public Managers in Spain

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Purpose / contribution

Nowadays, many public administrations are involved in processes of change, trying to improve its structure and functioning. Transparency is a capital part of this process, playing a relevant role in recruitment and assessment of applicants processes. In Spain, the recent legislation in force (i.e Estatuto Básico del Empleado Público, EBEP), specifically deals with the position of Public Manager in the administration demanding reliable, valid, effective, and fair processes and tools.
We have focused on a biodata instrument based on applicants' past experiences, behaviors and feelings in specific situations. Biodata has many advantages as their low cost, and validity, even their low faking.
Our study aims to identify a set of biodata for the assessment of public managers and to investigate their adequacy in terms of fairness and privacy.

Design / methodology

We have conducted a cross-sectional qualitative study with the participation of Public Managers from the area of Principado de Asturias (Spain).
The data gathering was performed in two stages. On the first stage, six focus groups (n = 12) decided which biodata were more relevant for the public manager positions. These focus groups were leaded by a member of the research team while other two members recorded the session coded and classified the information. These last two members compare their results till reach a very good agreement (K = .89).
The second stage, still in progress, is an evaluation of the biodata previously identified in according to three criteria, fairness, privacy, and validity, with a Likert scale from 1 (Totally disagree) to 7 (Totally agree). Results were analyzed with the classic statistical approach and with a fuzzy logic approach (a methodology designed to deal with problems in which the source of imprecision is the absence of sharply defined criteria of class membership). At this moment, we have the results of the pilot study with all the participants on the focus groups (n = 12), and just received questionnaire from a considerable amount of managers, around 250. In the following days we will have the final results of the second study.

Results

Despite of this research is still in progress, we have reached some preliminary results. First, 30 biodata were identified by the focus groups. Furthermore, the biodata could be classified in the following categories: (1) quality of experience, with 16 items; (2) managerial competences, with 4 items; and (3) proactivity and innovation, with 10 items.
Regarding the questionnaires, the fuzzy logic approach found eight biodata with enough support to be considered in further selection procedures.

Limitations

The results are provisional due to the research is still in progress, but it will be done in February 2016.

Implications
We have developed a new and valid method for analyzing biodata that could be generalizable to other instruments used in personnel selection.

Originality/value
A valid biodata instrument with a fuzzy methodology.

Notes:

The Dynamic Influence of Team-based Disruptions on Coordination and Performance in Sports Teams

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Purpose
A team must be able to adapt its strategies based on task-related changes as well as on changes in team structure through compensatory behaviours and reallocation of intra-team resources. Team constellations in sports teams are often not only dynamic over seasons due to player transfers but also over games due to sending-offs during the games. A lack of adaptation to such team-based disruptions (TBD) should result in less effective coordination patterns and a drop in performance. In this dynamic environment team coordination cannot be seen as a static process but rather as a balancing act of adaptive coordination in which nonlinear dynamics (ND) play a pivotal role. Research needs to explore how teams deal with changing team constellations (team familiarity), how they adapt their coordination processes, and how these adaptations affect performance. Therefore we are interested in how teams adapt their coordination to TBD and how team familiarity affects this relationship.

Methodology
This study relies on existing football databases and consists of teams of the English Premier League that were analysed over six seasons. 373 games with TBD in form of sending-offs (yellow-red/ red cards) were observed. Team familiarity was assessed by the average amount of time each player has played together with all the others. Coordination was measured using the amount of unsuccessful passes in relation to ball possession before and after the disruption occurred, while performance was assessed by the number of points a team achieved before and after the disruption. Using ND, (i.e. nonlinear regression techniques, time series analysis) seem appropriate to grasp the dynamical aspects of team familiarity and coordination patterns that the teams need to adapt to in order to improve or keep their performance stable.

Results
The dataset is complete and all necessary variables present. Data analysis is ongoing and we are using ND tools to analyse the dataset. We expect that TBD has a greater influence on coordination and performance in teams that are less familiar with one another than in teams that have been playing together for a longer time.

Limitations
Sample characteristics may limit generalizability. Nevertheless management literature increasingly regards sports teams as an appropriate model for work and organizational teams.

Implications
Our results should increase awareness about the effects of structural changes in teams and the influence on coordination and performance. Team familiarity might be an important factor to consider when managing a team. The research provides important practical advises for managers of sports teams and teams more generally on how to capitalize on team familiarity. Further applying NDS in form of nonlinear regression techniques and time series allows us to advance the field of work and organizational psychology from a methodological point of view.

Originality
The research contributes in significant ways to the to date scarce literature on the dynamics of team factors and their effects on coordination and performance over time. The proposed study advances the knowledge of team performance. The longitudinal design of the study allows a detailed analysis of influencing factors of coordination and performance.

Notes:

What Is it That They Do? A Qualitative Study of Engaged Teams' Verbal and Non-Verbal Interactions

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Purpose/Contribution
Engaged teams are highly motivated to work and persist even when facing difficulties, and share a positive affective environment. Theoretically, team work engagement emerges in teams that are able to successfully manage conflict, affect, and motivation of team members (Costa, Passos & Bakker, 2014). However, to what specific interactions do those processes correspond to? How exactly do teams "manage affect" or "build motivation"? We qualitatively analyze the verbal and non-verbal behavior of members of engaged teams, looking for patterns that characterize their interactions overtime.

Design/Methodology
Six teams (N = 31 individuals) were videotaped during a decision making task, for one hour. The videos were coded based on a priori defined categories. Non verbal behavior was analyzed considering the dimensions of the circumplex model of affect (Russel, 1980), following Bakker Oerlemans (2011) proposal that considers work engagement a highly active and positive state. The degree of team's activation and the valence of their interaction was coded, based on postural, facial and vocal indicators. In what verbal behavior is considered, the videos were coded in terms of motivational and affective processes, as defined by Marks, Mathieu and Zaccaro (2001) and operationalized by Costa et al. (2014). Team work engagement was assessed using questionnaires.

Results
High engaged team members seem to work physically close and have an increment on their interactions until the task's temporal midpoint. They have an initial peak/increase of activation followed by irregular ups and downs in activation, and an U-shaped temporal evolution of their emotional valence (with more positive emotional valence in the first and last moments). The most interpersonal processes used are affective, namely acceptance and positive engagement; and the most motivational processes include recursive positive feedback and highlighting the teams' wins in the first moments of the task.
High performing teams showed higher activation levels in the second half of the teams' task, as well as higher levels of affective processes over motivational ones. The worst performing team in the group had the highest initial interaction levels followed by an abrupt decrease both in their levels of interaction and in their levels of activation. Simultaneously, they presented higher peaks of positive emotional valence and an outstanding frequency of "acceptance".

Limitations
Considering the small sample size and the exploratory nature of the study, results must be perceived with caution and further research is needed to support their adequacy.

Implications
These results suggest that, although engaged teams are essentially characterized by the presence of positive interactions, it is fundamental to alternate more "exited" and fun moments with more task focused ones, and collective interaction moments with individual work. This dynamic changed from one mode to the other seems to allow to keep a functional balance between socio-emotional and

task areas.

Originality/value
Ee explored what patterns characterize highly engaged teams and take an in-depth, qualitative look at team interactions, considering really happens in teams during teamwork, answering Kozlowski and Chao’s (2012) call for studying the dynamics of emergence in a more direct way, different from the generalized linear models.

Notes:

Interest as a Moderator in the Relationship Between Challenge/Skills Balance and Flow at Work: An Analysis at Within-Individual Level

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Purpose/contribution
Considering flow as a non-ergodic process (i.e., non-homogeneous across individuals and non-stationary over time) that happens at the within-individual level, in this research we work with Bakker's model that propose flow as made up by three components: intrinsic motivation, enjoyment, and absorption. Taking into account that flow theory can be considered as an intrinsic motivation theory, and the recent proposals about the need to distinguish between pre-conditions of flow and the flow experience itself, we look at interest as a moderator between the challenge/skills balance and the experience of flow, rather than a component of the flow experience.

Design/methodology
A total of 3640 recordings were collected from a sample of 58 workers using an experience sampling method (several registers a day, during 21 working days). The data was analyzed using regression techniques in each participant (i.e., at within-individual level). Our work tries to respond to the following two research questions: Will interest play a moderating role in the relationship between challenge/skills balance and flow? Will a non-linear model (cusp catastrophe model) better explain the relationship among challenge/skills balance, interest, and flow?

Results
The results suggest that our hypotheses were correct: including interest as moderator better explains the relationship between challenge/skills balance and flow in comparison to a model without moderation (R^2 values change from 0,33 to 0,50). Additionally, carrying out the analysis following non-linear techniques explained more variance as well (R^2 = 0,67), and this increment was significant.

Limitations
To increment sample size and include an analysis of the different tasks that the worker is doing would be relevant for future research.

Implications
These results support the idea that interest should be considered as a key precondition for the appearance of flow, and this relationship is non-linear. We could say that these findings are exemplary in the field and brings up questions for their application in further research.

Originality/value
To apply nonlinear modeling at within-person level in order to study a non-ergodic process such as flow at work.

Notes:

Examining Dynamic Team Performance through Cusp Catastrophe Models

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Purpose/contribution

This article focuses on the discontinuities of team performance outcomes in self-management teams. The aim of this article is twofold: first, to identify possible discontinuities in team performance over time; and second, to determine whether episodic team processes (Marks, Mathieu & Zaccaro, 2000) and faultline strength (Lau & Murnighan, 1998) at early stages of the team performance cycle predict such discontinuities.

Design/methodology

We expect change in team performance over time will show linear and nonlinear variability, and that these can be better captured if framed under NDS theory. We argue that change in team performance can be better captured by means of a cusp catastrophe model, which simultaneously captures linear and nonlinear change in data distribution (Guastello, 2014; Zeeman, 1976). Participants in this study were 2249 individuals distributed across 502 self-managed teams, enrolled in a management game simulation during 5 weeks. Data analysis was done using the R software packages “asw.cluster” (Meyer & Glenz, 2013), and “cusp” (Grasman, Maas, & Wagenmakers, 2009).

Results

As hypothesised team performance growth is discontinuous, hence being better described through nonlinear modelling then through linear modelling ($\chi 2$ = 495.6, df = 2, p = 0). Our findings also suggest that action processes (B = .16, SD = .08, Z = 1.98, p = .05, 95% CI .00, .33), but not transition processes (B = -.00, SD = .07, Z = -.01, p = .99, 95% CI -.14, .14) and interpersonal processes (B = -.06, SD = .11, Z = -.53, p = .60, 95% CI -.27, .16), work as an asymmetry factor and are an initial conditions to team performance growth (R^2 = .59, p = .00, AIC = 940, BIC = 973.91). The results also show that team faultline strength is a bifurcation factor (B = -.13, SD = .06, Z = -2.02, p = .05, 95% CI -.25, -.00) and an initial condition to team performance growth.

Limitations

Although team performance was collected across five consecutive weeks, team performance growth was estimated as (Team performance time 5 – Team performance time 1)/Team performance time 1. Not only does this approach reduces variability (and discontinuity) in data distribution, as it renders a limited view of team performance change over time. Continuations of this study will test a structural equations model longitudinal cusp catastrophe approach proposed by Chow, Witkiewitz, Grasman and Maisto (2015).

Implications

This research contributes to the study of teams by showing evidence of teams as CAS. Furthermore, this study extends previous work on the discontinuities of team performance trajectories over time (e.g. Guastello, 2010) by showing that episodic teams’ processes and faultline strength contribute differently to how team performance changes over time.

Originality/value
This research is original and of interest for the EAWOP SGM on NDWOP because it studies the relationship between team processes, diversity faultlines and team performance through cusp catastrophe theory. This research echoes and extends previous work by others (Ramos-Villagrasa et al., 2012) on the chaotic nature of performance, and teams as CAS.

Notes:

k-centres Functional Clustering: A Person-Centered Approach to Modeling Complex Nonlinear Growth Trajectories

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Abstract

In the present paper, we introduce k-centres functional clustering (k-centres FC), a person-centered method that clusters people with similar patterns of complex, highly nonlinear change over time. We review fundamentals of the methodology and argue how it might respond to some of the limitations of the traditional approaches to modeling repeated measures data. The usefulness of k-centres FC is demonstrated by applying the method to weekly measured commitment data from 109 participants who reported psychological contract breach events. The k-centres FC analysis shows two substantively meaningful clusters, the first cluster showing reaction patterns with general growth in commitment after breach, and the second cluster showing general decline in commitment after breach. Further, the reaction patterns in the second cluster appear to be the result of a combination of two interesting reaction logics: immediate and delayed reactions. We conclude by outlining ideas for future organizational research incorporating this methodology.

Notes:

A Cusp Catastrophe Model for Team Learning, Team Social Cohesion and Team Culture

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Purpose/contribution
This paper examines team learning within a nonlinear dynamical system (NDS) perspective. Team learning could be conceived as a continuous process of reflection and action, characterized by behaviors like seeking feedback, exploring, experimenting, reflecting, and discussing errors (Edmondson, 1999). Research has successfully identified conditions that promote learning process in teams. It has been shown that, among other variables, team culture (members' beliefs about "the way things are done" in the group) could have this kind of influence (Rebelo, Stamovlasis, Lourenço, Dimas, & Pinheiro, in press). Team cohesion has been also identified as a supporting condition for team learning (Bell, Kozlowski, & Blawath, 2012). Different types of cohesion have been distinguished, such as task and social cohesion (Mullen & Copper, 1994).
According to Van den Bossche, Gijselaers, Segers, & Kirschner (2006), task cohesion is a supporting condition of team learning behaviors. However, the relationship of social cohesion (the emotional bonds, such as liking, sense of belonging and caring among group members) with learning behaviors seems more complex. It could promote learning behaviors because it increases the willingness to help each other, but high social cohesion could also lead to uncritical acceptance of solutions. The studies reviewed by Bell et al. (2012) pointed to the same direction. The complex relationship between social cohesion and team learning behaviors led us to study it under the NDS framework, in order to analyze social cohesion as a bifurcation variable, using cusp catastrophe modeling.

Design/methodology
This research is based on a sample of 44 project workgroups, where data were collected at two moments of their life cycle (half-time and end), with single-item visual analogue scales. Convergent and nomological validity studies were carried out, revealingsatisfactory psychometrics qualities of these measures.
Using the dynamic difference equations model (Guastello, 2011) this research proposes a cusp catastrophe model for explaining team learning, implementing team culture as the asymmetry variable and social cohesion as bifurcation.

Results
We analyzed four types of team cultural orientation as asymmetry variable (support, innovation, rules and goals). In all situations, the cusp model (Adj R^2 ranging from .48 to. 37) is superior to the pre-post linear model. Also the cubic term, the bifurcation effect and the asymmetry term are statistically significant. Thus, the findings support the presence of a cusp structure in the data, revealing that a nonlinear effect is taking place in the process of team learning. Social cohesion acts as a bifurcation factor, that is to say, beyond a certain threshold of social cohesion, groups that have the same cultural orientation might oscillate between two attractors, the modes of high and low learning behaviors respectively.

Limitations, implications, and originality/value

Despite the small sample size, this study contributes to the small group research literature by presenting a functional role for social cohesion as bifurcation, which might explain the discrepancies between various findings of social cohesion on team learning behaviors. This study also suggests that teams should be aware that high social cohesion may lead members to avoid team learning behaviors, such as the exploration of different opinions or error discussion.

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Notes:

Personnel Selection Algorithm Using Fuzzy Analytic Hierarchy Process – a Dynamic Decision-Making Approach

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Abstract

Personnel Selection is a human resource management problem, which leads difficulties in allocating scorings to the criteria during decision making. Dynamic decision-making represents interdependent decision-making in a time dependent dynamic context. Dynamic decision-making process is both dependent of the previous actions or events that are outside of the control of the decision maker, making it a complex process. Fuzziness is the main characteristic of personnel selection. Thus, the present work conducted fuzzy analytic hierarchy process (FAHP) to develop a robust personnel selection model. The proposed model is described and validated on the existing data of a multinational industrial company from Arad. The model used as input variables data from the selection interview. The main hypothesis of this work established that the FAHP is superior to the classic model when calculating the final scores obtained by the candidates at the interview. The difference between the two models depicted that the hierarchy provided by the classic method may place several candidates on the same position, while the FAHP method places each candidate on different position. FAHP superiority is demonstrated by analyzing the hierarchy of candidates in both models classic and FAHP, related to the subsequent job performance hierarchy. The proposed approach proved that the association degree between the interview FAHP score and the subsequent job performance was significantly increased. The results demonstrated the superiority of FAHP over the classic method for assessing candidates in an interview.

Key words: Analytic hierarchy process (AHP), Fuzzy sets, Fuzzy analytic hierarchy process, Human capital, Personnel selection

Notes:

A Dimensionality-Reduction Algorithm for Accurate Visualization of Personal Relationships Within a Team

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Understanding relationships among team members is a difficult yet important task for all leaders. The number of relations grows quadratically with the number of members. Although social network analysis tools provide valuable insights to experts, they are difficult to understand for professionals. Our aim was thus to develop a method that would 1) convey the structure of relationships as accurately as possible (accuracy), and 2) be readily comprehensible for all professionals (comprehensibility).

The method consists of transforming relational data in the form of an adjacency matrix of directed weighted graph (obtained, for example, from a questionnaire in which every person rates every other person in some relational aspect, e.g. frequency of communication) into a 2D plane (a "sociomap") so that the distance between people on the sociomap and the relative distance between people in the original data are as similar as possible. Technically, we developed a simulated annealing algorithm that searches for positions that maximise Spearman correlation coefficient between ranked distance among people on the sociomap and ranked data from the perspective of each person. Since the adjacency matrix for n people forms essentially an n-dimensional space, its transformation into 2D plane can almost never be perfectly accurate and the optimal solution cannot be found analytically.

To assess the accuracy, we compared the results of our positioning algorithm to results of two widely used dimensionality-reduction techniques: principle component analysis (PCA) and multi-dimensional scaling (MDS). Measured for various numbers of people, our algorithm performed significantly better than the alternative techniques, measured by the optimization criterion – the Spearman correlation between ranked euclidean distance on the map and in the adjacency matrix.

This criterion was chosen on the grounds of comprehensibility: to maximally exploit the embodied metaphor of personal distance and spatial distance. People readily understand the analogy between social and spatial proximity.

To assess the comprehensibility, we tested 1) the ability to recall the social structure, 2) the ability to interpret the social structure when visualized as a sociomap without any prior information about how to interpret the visualization. The ability to recall the social structure was measured as the ability to recreate the adjacency matrix after either seeing a sociomap or the matrix itself. As a result, we found that people have better memory of the social structure when it is presented visually as a sociomap than when it is presented as a matrix of data. Regarding the second point, we found that the intuitive understanding of the social structure (measured by a proficiency questionnaire designed for that purpose) was very good and the results are not influenced by sex or age.

Notes:

Examining Intra-Individual Variability in Emotions in Workplace Bullying Victims and Non-Victims: A Diary Study

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Introduction
Negative emotions are one of the fundamental consequences of workplace bullying (WB).
The aim of this paper is twofold: first, to compare the prevalence and intensity of the emotions that workplace bullying victims and non-WB victims experience when facing conflicts at work. Second, to investigate the Healthy Variability hypothesis, according to which emotions in WB victims should fluctuate less over time as a signal of unhealthy behaviour in comparison to non-WB victims.

Methodology
We designed a diary study to analyse how emotions fluctuate over time in both victims and non-victims of workplace bullying. A group of 47 victims and 65 non-victims were identified based on a questionnaire time 1 and time 2 (time lag of 6 months). Positive and negative emotions were assessed between time 1 and time 2 using an event based diary study that was filled out for a period of two times 20 working days with a break of 4 months in between. Affect spin was used to compare intraindividual variability in emotions.

Results
The results showed that WB victims experienced negative affect more intensely in comparison with non-WB victims, and this difference was statistically significant. Furthermore, affect spin was similar for both victims and non-victim's groups.

Discussion
The present study is one of the first in using event based diary data, and confirms previous cross-sectional research and extends those findings.

Keywords: workplace bullying, affect spin, emotions, diary studies, healthy variability hypothesis.

Notes:

Relating Neuroticism to emotional Exhaustion: A Dynamic System Approach to Personality

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Although previous research on within-person fluctuations has provided some initial insights into the intrinsic dynamics of individual differences, our understanding of the processes underlying personality is still limited at best. Moreover, this process approach to personality –which focuses within-person fluctuations– has been developing relatively independent from the structural approach to personality –focusing on between-person fluctuations–. Recently, however, researchers started to realize that, if we really want to understand personality, an integrative approach is to personality is needed (Judge, Simon, Hurst, & Kelley, 2014). In the present study we provide such an integrative approach by conceptualizing personality as a non-linear dynamic system. In particular, we propose a model of personality [PersDyn] that captures growth and novelty in the emerging patterns of personality states using three components: (1) the average level of the states [baseline], (2) the extent to which people experience different states [variability], and (3) the swiftness with which they return to their baseline once they deviated from it [attractor strength]. To illustrate this approach, we apply the PersDyn model to the study of the relationship between neuroticism and emotional exhaustion.

We conducted a five-day experience sampling study in which 89 employees were asked to report their level of state neuroticism six times per day using the 8-item neuroticism Mini Marker scale (Saucier, 1994) (N = 4726). Emotional exhaustion was measured at the end of the study using the UBOS-A burnout scale (Schaufeli & van Dierendonck, 2001). The state neuroticism data were modelled using the Bayesian Hierarchical Ornstein-Uhlenbeck model (BHOUM; Oravecz, Tuerlinckx, & Vandekerckhove, 2016) - a mathematical framework of temporal change for phenomena with regulatory forces, which is based on stochastic differential equations and combines both deterministic control and stochastic variability. Using the BHOUM model we obtained for each participant an estimate for his/her baseline level of neuroticism, his/her level of neuroticism variability, and his/her neuroticism attractor strength, and we related these parameters to the emotional exhaustion scores.

Results showed that people with a higher level of baseline neuroticism were more likely to suffer from emotional exhaustion. Similarly, higher levels of variability were related to increased levels of emotional exhaustion. Finally, we found an interaction effect between baseline neuroticism and attractor strength: Especially people with a high baseline and high attractor strength were likely to experience a high degree of emotional exhaustion, whereas people with low levels of baseline neuroticism were less likely to suffer from exhaustion if their attractor strength was high. The results from our study present valuable insights into the psychology of personality by showing that in order to fully understand personality, it is essential to take into account not only the trait level, but also the more dynamic components of personality. Moreover, despite the major complexity of the personality system, our model offers a straightforward way to examine how it evolves over time in non-linear, yet meaningful ways. Finally, the proposed dynamic systems model can be extended beyond personality to examine other complex phenomena, such as work performance or emotions at work.

Key words: Personality, non-linear dynamics, dynamic systems, neuroticism, emotional exhaustion

Notes:

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APPENDIX

Data Analysis with Structural Equations[1]

The method of structural equations that is described in the PowerPoint file in Menu 1[2] can be executed on standard statistical packages such as the *Statistical Package for the Social Sciences* (SPSS). A brief instructional guide for accomplishing those analyses is presented here. Instructions are specified in terms of statements that can be used in a mainframe SPSS program. The same commands can be used in the PC versions with only minor modifications; the mainframe syntax is easier to explain, however.

Note the use of the term "structural equations" is consistent with the mathematical definition thereof. The procedures listed below do not involve Linear Structural Relations Analysis (LISREL) or its later versions that allow some types of nonlinear analysis.

CATASTROPHE MODELS WITH POLYNOMIAL REGRESSION

The data set for catastrophe models needs to be organized so that each observation contains the dependent measure (the variable that is hypothesized to show catastrophic behavior) at two points in time, and the values of the control value at Time 1. The user then needs to specify some COMPUTE statements before specifying the actual regression sub-program. COMPUTE statements are needed to transform dependent measures and other control variables with respect to location and scale.

```
COMPUTE z2 = (y2 – L)/ S
```
(A1)

In statement A1, *y2* is the dependent measure at Time 2, *L* is the value of location, and *S* is the value of scale. Actual numbers would replace *L* and *S*. The same syntax would be used for control variables and for changing $y_1 \rightarrow z_1$. Compute statements are also needed to define power terms such as z^3 (statement A2), a similar quadratic term, bifurcation interactive terms (A3), and the difference score (A4) that is used as the dependent measure in the catastrophe models.

```
COMPUTE zpow3 = z1**3
```
(A2)

```
COMPUTE bz = b*z1
```
(A3)

```
COMPUTE deltaz = z2 – z1
```
(A4)

The variable *b* listed in statement A3 is a variable that is hypothesized to function as a bifurcation term in a cusp. A particular application can have several variables called *b*. The variable called *a* in statement A5 is a variable that is hypothesized to function as an asymmetry variable.

Proceed to the main program statements after completing the COMPUTE statements. Use the regression sub-program.

```
Regression descriptives/ missing=pairwise
      /variables = dz zpow3 zpow2 bz a
      /dependent = dz/ enter zpow3 zpow2 bz a
```
(A5)

---

[1] Portions of this text are adapted from: Guastello (2002 Appendix A).

[2] "Resources for students and teachers," www.societyforchaostheory.org/tutorials

Next inspect the significance tests for each of the terms in the model. If there the regression weight for `zpow3` is not significant, drop `zpow2` and try it again. In the event that there are several variables being tested as *a* and *b* variables, drop any variable for which the *p*-value on the regression weight is greater than 0.10. Then try the reverse hypothesis, that the variables first thought to behave as *b* are really *a*'s and vice versa. To do so define some more compute statements for the new bifurcation terms (A6) and run the regression as a two-step process (A7).

```
COMPUTE az = a*z1                                                  (A6)
```

```
REGRESSION descriptives/ missing=pairwise                          (A7)
      /variables = dz zpow3 zpow2 bz a b az
      /dependent = dz /enter zpow3 zpow2 a  /enter az b
```

Statement A7 assumes that the variable that was first thought to behave as *b* was not significant, and that both `zpow3` and `zpow2` were acceptable:

Finally, the two linear alternative models would be defined as A8 and A9:

```
REGRESSION  descriptives/ missing=pairwise                         (A8)
      /variables = dz b a
      /dependent = dz /enter a b
```

```
REGRESSION descriptives/ missing=pairwise                          (A9)
      /variables = z2 z1 b a
      /dependent = z2 /enter z1 b a
```

EXPONENTIAL SERIES WITH NONLINEAR REGRESSION

Nonlinear regression offers much greater flexibility in the definition of models compared to polynomial regression and its variations on the GLM. Because of its flexibility in defining a model, the nonlinear regression sub-program of SPSS requires a more specific statement of the intended models, and there is little automatic processing with regard to putting variables in or out of the model.

The data set up requires that the observations be ordered in time series, where each subsequent string of data represents observations at successive points in time. The control program again requires COMPUTE statements, but not generally as many. The definitions of $y \rightarrow$ z go in first along with the conversions for any control variables. Define the z as z_2 (statement A10) then use the LAG syntax to define z_1 at a lag of 1 time period (A11).

```
COMPUTE z2 = (y – L) / S                                           (A10)
COMPUTE z1 = lag(z2, 1)                                            (A11)
```

Next we define the three program statements for nonlinear regression. All three begin in the left-most space of the line; there is no indentation on the second or third command. The first line specifies the variables that will appear in the model as nonlinear regression weights. Nonlinear regression is an iterative calculation process whereby the user specifies some initialized values of the regression weights (*a*, *b*, and *c* in this example). The program then fits the initial values with the model function to the data, makes an adjustment, then fit the result to the derivative of the function, makes an adjustment, then re-fits the principal model to the data again, and so forth, until the resulting corrections become trivial.

```
MODEL PROGRAM a = 0.5, b = 0.5, c = 0.5                            (A12)
```

It is usually good to specify initial values of the regression weights that are close to the final values, if the final values are known. I usually use 0.5 for initial values of all parameters in these studies. I have experimented (or rather fiddled) with possible strategies for using different initial values, but I have not yet found any strategy better than the equal estimates where nonlinear dynamics are concerned.

The second specifies the nonlinear model,

```
COMPUTE PRED = a*exp(b*z1) + c
```
(A13)

The third specifies the dependent measure and executes the program,

```
NLR z2 with z1
```
(A14)

The output from an example analysis corresponding to A13 appears in the last two pages of this document. For a recent exposition of the exponential modeling technique and an elaborate example involving two order parameters, see Guastello, Nathan, & M. Johnson (2009). For a verification of how well the technique performs in determining the fractal dimension of classic chaotic attractors, see T. Johnson and Dooley (1996).

Nonlinear regression programs sometime offer options such as constrained nonlinear regression or different methods of specifying error terms. Constrained nonlinear regression keeps the parameter estimates within certain boundary values, which are typically chosen based on previous studies of similar functions with similar data. In the absence of any good reason to constrain values one way or another, I recommend using the unconstrained nonlinear regression, which is specified in statement A14 by the command NLR.

Another option allows the user to select of the principle of maximum likelihood for calculating the error component of the regression model instead of the principle of least squares.

Contrary to what some people seem to think, however, there is no particular association between maximum likelihood and nonlinear modeling and least squares with linear modeling; both can be used in either type of regression, although it’s true that linear regression with maximum likelihood is much less common than the least squares method.

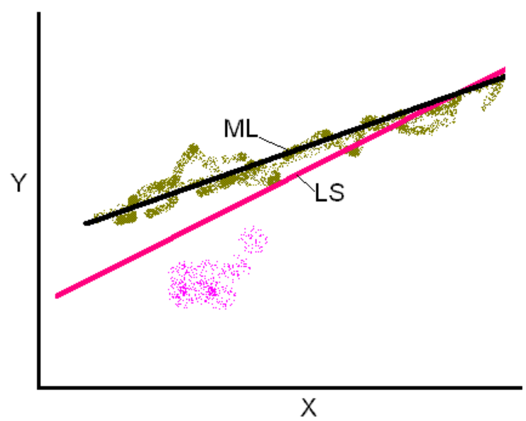

Fig. 1. The methods of least squares and maximum likelihood would place the line differently in the face of messy (pink) data.

Figure 1 illustrates how the two procedures would behave differently if they were looking for a line in messy data. The method of least squares, which is based on the principle of minimizing the squared distance from the regression line, would place the line in the location shown as LS. The method of maximum likelihood, however, would fit the line according to locations of greatest density, and thus place the line differently. Least squares would recognize the presence of the anomalous data points shown in pink, while maximum likelihood would essentially ignore them. For messy data, maximum likelihood might indeed have a greater chance of finding a good line where other events are occurring, but it does capitalize on chance. Least squares might have difficulty finding the line, but the line it would find would be more apt to generalize to situations where “pink data” are likely to occur again. For this reason some nonlinear analysts prefer the least squares technique. I would make the same recommendation; if you can find what you are looking for using least squares, the prognosis for generalizing out the original sample is greater and there is not much need to use alternative methods.

The nonlinear regression analysis concludes with an ANOVA table and a value of R^2 for the model overall. Tests on the specific regression weights are listed by SPSS as estimated values and their confidence intervals at the 95% level. If the upper and lower boundaries of the confidence interval are both positive or both negative for a particular regression weight, then the confidence does not include 0.00, and the results can be interpreted as significant at $p < .05$.

The weight on the exponent is the critical element of the analysis. In the event that statistical significance is not obtained for that weight, proceed to delete the less essential components from the models, namely, the constants. Statements A12 and A13 change to A15 and A16, respectively, while A14 remains the same:

```
MODEL PROGRAM b = 0.5                                   (A15)
COMPUTE PRED = exp(b*z1)                                (A16)
NLR z2 with z1                                          (A14)
```

To test the bifurcation model, Statements A12 and A14 remain the same, and A13 becomes A15.

```
COMPUTE PRED = a*z1*exp(b*z1) + c                       (A15)
```

Finally, there are times in which a nonlinear regression model fits so poorly that a negative R^2 is produced. Those values should be interpreted as equivalent in meaning as .00, meaning that the model fit was extremely poor.

CATASTROPHE PDFS WITH NONLINEAR REGRESSION

The method of testing catastrophe models by analyzing probability density functions (pdfs) through nonlinear regression is preferable, or should I say inevitable in two types of conditions: (a) The data are only measured at one point in time, but a catastrophe model is thought to exist therein nonetheless (e.g. in survey data, Smerz & Guastello, 2008), or (b) all time-1 measurements are 0.00 (e.g. in leadership emergence studies, Guastello & Bond, 2007).

Catastrophe models can be tested at two levels through the nonlinear regression procedure (a) the pdf only with no hypothesis about the control variables, and (b) with hypotheses about the control variables.

PDFs Without Control Variables

The test for the catastrophe pdfs is not substantially different from the exponential regression models just considered. There are two additional steps in data preparation, however. The first step requires a frequency distribution on the raw scores of the dependent measure, *y* that will produce the cumulative probability (or percentile) of *y*. Second, use a RECODE command to substitute the cumulative probabilities of *y* for *y* and give the result a new variable name, PCTY (A16).

```
RECODE Y (0 = .500) (1 = .617) (2 = .683) (3 = .725)                (A16)
      (4 = .750) (5 = .775) (6 = .800) (7 = .825) (8 = .842)
      (9 = .842) (10 = .883) (11 = .933) (12 = .950) (13 = .967)
      (14 = .999) (15 = .999) (16 = .999) into PCTY
```

The decimal values shown in A16 were those that were actually used in the leadership emergence study by Zaror and Guastello (2000) in which we were looking for a swallowtail catastrophe pdf. We still need to convert *y* to *z*. SPSS sometimes encounters an computational overflow when running nonlinear regression if, on one of the iterations, the numerical argument to the exponent exceeds 88. The problem is solved by multiplying *S* by 100 as shown in A17.

```
 COMPUTE z = (Y - L)/(S * 100)                                         (A17)
```

We can now proceed to the three statements for the nonlinear regression model. A19 is testing for the shape of the pdf only, and does not include the control variables. The control variables are essentially treated as constants and they are absorbed into the regression weights designated below as *a*, *b*, *c*, *d*, and *e*. Adaptations for testing the control variables are described later on.

```
MODEL PROGRAM  x= 0.5, a= 0.5 b=0.5 c=0.5 d=0.5 e=0.5               (A18)
COMPUTE PRED = x*exp(a*(z**5)+b*(z**4)+c*(z**3)+d*(z**2)+e*z)       (A19)
NLR PCTY with z                                                     (A20)
```

In the event that statistical significance is not obtained for each of the regression weights, the least essential element in the model can be dropped. In this case we would drop "`b=0.5`" from A18, and "`+b*(z**4)`" from A19; A20 would not change.

To test a cusp model instead of a swallowtail, substitute A21for A19:

```
COMPUTE PRED = x*exp(a*(z**4)+b*(z**3)+c*(z**2)+d*z)                (A21)
```

Determining Critical Points

Sometimes one is interested in the critical points associated with the catastrophe models – the values of the equilibria (attractor modes) and the repellor (statistical antimode). The critical values can be solved analytically by using the estimated parameters for *a*, *b*, *c*, *d*, and *e*, taking the second derivative of the argument to the exponent, setting it equal to 0.00, and solving for the roots. A regression program can do the job much more easily, however, than solving a differential equation by hand. To begin, create a data set that contains two columns: *Y* and the Frequency of *Y*, based on the frequency distribution was the previously obtained.

The analysis is a polynomial regression of Frequency of *y* as a function of *y*. The PSI-PLOT program (from Poly Software International) can perform the analysis instantly with a point-and-click to polynomial regression. The job can be done through SPSS, nonetheless. In either case, the conversion of *y* to *z* is not necessary for this type of problem. First compute polynomials of y^2, y^3, and y^4 using the syntax given in Statement A2. Then define the regression program to enter the polynomials from lowest to highest.

```
REGRESSION descriptives /missing = pairwise                         (A22)
      /variables = FREQY, y, ypow2, ypow3, ypow4
      /dependent = FREQY
      /enter y /enter ypow2 /enter ypow3 /enter ypow4
```

For data such as the leadership emergence data, there were only 17 values of *y*, so it was no surprise that all power polynomials showed statistical significance. The objective here is point estimation, however, rather than determination of significance. The regression results give regression weights that can be used to compute a predicted frequency of *y*. A plot of the predicted frequency of *y* gives the underlying modes and antimodes for the frequency distribution.

Testing Control Variables in Catastrophe Models

The early means of testing control variables in catastrophe models with nonlinear regression (Cobb, 1981) was indirect. The procedure first determined the cusp pdf, then produced parameter estimates for all observations. Then, as a separate step, it would calculate linear correlations between the hypothesized control variables and the parameter estimates associated with bifurcation and asymmetry. The matrix of correlations can be interpreted in much the same way as one would interpret the results of a factor analysis, where some research variables would "load" on one control parameter, and other variables would load on the other.

One limitation of the indirect strategy is that the R^2 for the model would only pertain to the pdf itself, and not include the impact of the control variables. Control variables, if they were placed in the model would, incidentally, have the effect of lowering the overall R^2 a bit because they are only imperfectly related to the parameter estimates. Another limitation is that the indirect method does not allow for point estimation except perhaps in a clumsy manner.

Thus we move on to a direct method for testing control variables as part of the catastrophe model. It helps enormously to have a clear hypothesis for the entire catastrophe model, and not simply the shape of the model. If the research situation lends itself to many possible variables that could be control variables, it is advisable to factor analyze them first, and then work with the common factors. For an example where factor analysis helped the cause, see Guastello and Bond (2007).

The nonlinear regression procedure involves only a small adaptation to what was presented already. For a cusp, let V_1 and V_2 represent hypothesized control variables for asymmetry and bifurcation respectively. A21 then becomes:

```
COMPUTE PRED = x*exp(a*(z**4)+b*(z**3)+c*V2*(z**2)+d*V1*z)
```
(A23)

For a swallowtail model, we would also have a control variable V_3 for bias. Thus A19 becomes:

```
COMPUTE PRED = x*exp(a*(z**5)+b*(z**4)+c*V3*(z**3)+d*V2*(z**2)+e*V1*z)
```
(A24)

In A23 and A24, the SPSS variable name would be substituted where V_1 V_2 and V_3 are shown.

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```
MODEL PROGRAM A = 0.5 B = 0.5 C = 0.5
COMPUTE PRED = C*COUNT1*EXP(A*COUNT1) + B
NLR DZ WITH COUNT1
```

All the derivatives will be calculated numerically.\ 15-Apr-97 group a output Page 12
17:50:05 MARQUETTE UNIVERSITY on VMSE:: VMS V6.1

There are 162 cases. There is enough memory for them all.

Iteration	Residual SS	A	B	C
1	34413.45162	.500000000	.500000000	.500000000
1.1	1654.164808	.535498891	.689669977	-.11180897
2	1654.164808	.535498891	.689669977	-.11180897
2.1	329.1820886	.399341095	.656138039	-.09518224
3	329.1820886	.399341095	.656138039	-.09518224
3.1	181.6668010	.114422615	.799534853	-.17552659
4	181.6668010	.114422615	.799534853	-.17552659
4.1	264.0394886	-.29864017	1.24107651	-.56618981
4.2	178.5112583	.059836957	.726913291	-.21507161
5	178.5112583	.059836957	.726913291	-.21507161
5.1	177.3947613	-.03784394	.896213429	-.34302024
6	177.3947613	-.03784394	.896213429	-.34302024
6.1	174.8474605	-.10389466	1.10702304	-.53978688
7	174.8474605	-.10389466	1.10702304	-.53978688
7.1	172.7339240	-.14676365	1.32262688	-.76300740
8	172.7339240	-.14676365	1.32262688	-.76300740
8.1	172.2111144	-.19116688	1.59126331	-1.0560150
9	172.2111144	-.19116688	1.59126331	-1.0560150
9.1	171.6498297	-.18500655	1.60671981	-1.0806820
10	171.6498297	-.18500655	1.60671981	-1.0806820
10.1	171.6495785	-.18500726	1.60551662	-1.0791883
11	171.6495785	-.18500726	1.60551662	-1.0791883
11.1	171.6495785	-.18500729	1.60551674	-1.0791885

Run stopped after 23 model evaluations and 11 derivative evaluations.
Iterations have been stopped because the relative reduction between successive
residual sums of squares is at most SSCON = 1.00E-08

Nonlinear Regression Summary Statistics Dependent Variable DZ

Source	DF	Sum of Squares	Mean Square
Regression	3	37.62595	12.54198
Residual	159	171.64958	1.07956
Uncorrected Total	162	209.27553	
(Corrected Total)	161	209.20959	

R squared = 1 - [Residual SS / Corrected SS] = .17953

Parameter	Estimate	Asymptotic Std. Error	Asymptotic 95 % Confidence Interval Lower	Upper
A	-.185007292	.056955741	-.297494665	-.072519919
B	1.605516744	.403831106	.807951839	2.403081650
C	-1.079188522	.422936783	-1.914487067	-.243889978

15-Apr-97 group a output
Page 13
17:50:07 MARQUETTE UNIVERSITY on VMSE:: VMS V6.1

Asymptotic Correlation Matrix of the Parameter Estimates

	A	B	C
A	1.0000	-.7024	.9016
B	-.7024	1.0000	-.9285
C	.9016	-.9285	1.0000