The rough journey to success: Examining the nonlinear dynamics of processes and performance in teams

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RUNNING HEAD: Performance Dynamics

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Abstract: We build on the Nonlinear Dynamic Systems (NDS) theory to examine if team performance change across a complete performance cycle is nonlinear and if such change is related with team processes changes over time. Participants were 214 teams enrolled in one management competition. The hypotheses were tested using nonlinear regressions and catastrophe modeling. The results of the nonlinear regression model support the hypothesis that change in team performance over time follows a cusp catastrophe distribution, $R^2_{Cusp} = 93$, $F(5, 1065) = 16889.82$, $p < .001$*; and that team processes do function as asymmetry (transition and action processes) and bifurcation (interpersonal processes) factors. Finally, the results of the maximum likelihood model also suggest that the cusp catastrophe model (*$R^2 = .68$*) explains team performance better than the linear (*$R^2 = .05$*) and logistic models (*$R^2 = .07$*). This study reiterates the importance of incorporating the NDS perspective within the teamwork literature to leverage our knowledge about the way teams perform over time.*

KEYWORDS: team processes, team performance, nonlinear dynamic systems; cusp catastrophe models.

INTRODUCTION

Twenty years ago, Arrow, McGrath and Berdahl (2000) published the theory of small groups as complex adaptive systems (CAS). Their ideas offered the opportunity for a unifying theory of group behavior in the workplace and yet, in the years that followed its publication, few studies have explicitly integrated CAS principles and methodologies (Ramos-Villagrasa, Marques-Quinteiro, Navarro, & Rico, 2018).

Evidence of the view of small groups as CAS lies in research within the Nonlinear Dynamic Systems (NDS) perspective (Hackman, 2012), which is the study of *complex systems.* These are self-organizing systems sensitive to initial conditions, i.e., small changes in a system's characteristics can cause dramatic change later on (Guastello & Liebovitch, 2009). Examples of self-organization can be taken from empirical studies about emergent leadership (e.g., Guastello, Zygowicz, & Bock, 2005), team coordination (e.g., Amazeen, Stevens, Galloway, & Gorman, 2014), and interpersonal synchronization of behavioral and physiological activity (e.g., Gipson, Gorman, & Hessler, 2016), showing how self-organizing processes are positively related with better team outcomes. For instance, research by Vink, Wijnants, Cillessen and Bosman (2017) suggests that interpersonal synchronization was also negatively related with task performance, thus reiterating the importance of having a loosely-couple system to enable self-organization in complex learning environments.

Several scholars have argued that using the NDS perspective offers researchers grand opportunities to study teamwork and team outcomes and have reasoned in favor of their implementation (e.g., Hackman, 2012). Indeed, an accumulating body of research suggests that variables like team performance behave chaotically over time (e.g., Guastello & Guastello, 1998; Guastello, 2010; Marques-Quinteiro, Rico, Passos, & Curral, 2019a). As an example, Ramos-Villagrasa, Navarro and Garcia-Izquierdo (2012) found that the best performing basketball teams over twelve seasons were not the ones displaying linear performance trajectories but rather the ones whose performance over time had chaotic variation. The theory of small groups as CAS acknowledges team processes as emergent phenomena and a fundamental driver of the self-organizing and adaptation leading to team performance (Arrow et al., 2000), which is also in line with the taxonomy of team processes developed by Marks, Mathieu and Zaccaro (2001). For these authors, team processes are "team members' interdependent acts that convert inputs into outputs that are relevant to achieve collective goals" (Marks et al., 2001, p. 357) and can be divided into three types: transition, action and interpersonal processes (Mathieu, Luciano, D'Innocenzo, Klock, & LePine, 2019a). While meta-analytical evidence suggests a positive relationship between all team processes and team performance (LePine, Piccolo, Jackson, Mathieu, & Saul, 2008; Mathieu, Gallagher, Domingo, & Klock, 2019b), Marks et al. (2001) argued that "*whereas transition and action processes have a natural temporal rhythm and relationship to one another, the interpersonal processes can work as an attribute or a liability throughout the goal accomplishment episodes*" (p. 369). Marks et al. (2001) assumption suggests that change in team processes over time contributes to team performance, although in different ways. While transition and action processes are linearly related with team performance, interpersonal processes are nonlinearly related with team performance. Within the NDS framework, one methodology that offers mathematical capabilities to study teamwork dynamics in a way that linear and nonlinear change are simultaneously regarded, thus further expanding current knowledge of the relationship between team processes and team performance is cusp catastrophe modeling (Zeeman, 1979).

Cusp catastrophes are a set of mathematical equations describing nonlinear behavior in cases where two control parameters (independent variables) define the nonlinear dynamics of one order parameter (dependent variable). Previous studies have successfully applied cusp catastrophes to the study of teamwork phenomena (e.g., Dimas, Rebelo, Lourenço, & Rocha, 2018; Guastello, Correro II, & Marra 2019; Marques-Quinteiro et al., 2019b; Rebelo, Stamovlasis, Renato, Dimas, & Pinheiro, 2016). For instance, Guastello et al. (2019) found that the cusp catastrophe models of workload and fatigue were more accurate for describing nonlinear trends in team performance compared to linear models.

In the current study, we extend previous research on the relationship between team processes and team performance (e.g., Mathieu et al., 2019b), while testing the new hypothesis that distinct team processes (Marks et al., 2001) contribute to the dynamics of team performance in different ways. We also contribute to scientific research on teams by analyzing what happens in teams over time (i.e., their team processes) and how the complex interactions of different processes (i.e., action, transition and interpersonal) and performance can be described more precisely using nonlinear models (i.e., cusp catastrophe model). Finally, this study also integrates the temporally based framework of team processes (Marks et al., 2001) within the NDS perspective (Guastello & Liebovitch, 2009), to assist in the consolidation of the theory of small groups as CAS (Arrow et al., 2000) and the integration of time in team research (Mathieu et al., 2019b).

THEORETICAL BACKGROUND

According with Marks et al. (2001), teams perform in cycles that unfold across performance episodes with distinct time lengths. During performance episodes, teams move between transition and action phases where they engage in planning and evaluating activities (transition phase), and task execution activities (action phase). Marks et al. also describe three kind of processes that are necessary to help teams successfully navigating across performance episodes: transition, action, and interpersonal processes. Team *transition processes* regard those processes that are needed for task organizing, which include: (1) mission analysis formulation and planning, (2) goal specification, and (3) strategy formulation. Team *action processes* regard those processes that allow the plan outlined during transition processes to be implemented, which includes (1) monitoring progress toward goals, (2) systems monitoring, (3) team monitoring and backup behavior, and (4) coordination among team members and their actions. Finally, team *interpersonal processes* regard those processes in which team members engage in order to promote (and preserve) positive team member interactions. These include (1) conflict management, (2) motivation and confidence building regarding the mission accomplishment, and (3) affect management.

The relevance that team processes have to researchers and practitioners is that team processes are the drivers of change and the main antecedents of team performance (i.e., the extent to which a team accomplishes its tasks successfully; Hackman, 1987). This idea also finds echo in the leadership literature, namely, Fleishman's Leadership Theory (e.g., Fleishman & Simmons, 1970) and the notion that effective leadership should primarily enable transition and interpersonal processes in teams, by engaging in consideration (i.e., "the extent to which an individual is likely to have job relationships with his subordinates characterized by mutual trust, respect for their ideas, consideration of their feelings, and a certain warmth between himself and them", p. 170) and structure (i.e., "the extent to which an individual is likely to define and structure his own role and those of his subordinates toward goal attainment", p. 170).

Whereas existing studies offer a good account of the relationship between team processes and team performance (e.g., LePine et al., 2008; Mathieu et al., 2019b), further insightful knowledge into the dynamic nature of team processes could be created if phenomena were examined from a temporal perspective (Maynard, Mathieu, Rapp, & Gilson, 2012). Understanding *how* team processes evolve and unfold over time and *how* are they related with team outcomes (i.e., performance) can be better understood if the focus is in *how* and *when* processes change, and *how* and *when* does change cause different team outcomes

(Maruping, Venkatesh, Thatcher, & Patel, 2015; Maynard et al., 2012; McGrath, 1991; Roe, 2008; Santos, Uitdewilligen, & Passos, 2015).

Frequently scholars have examined team processes longitudinally as one single aggregated construct (e.g., Maruping et al., 2015), and the relationship between pairs of team processes (e.g., Matheiu & Shulze, 2006) as well. However, Marks et al. (2001) propose that different team processes are critical at different phases of task execution and episodic processes can co-occur as a way to help the team dealing with multiple goals (Marks et al., 2001; McGrath, 1991). Although previous contributions have looked at how change in team processes such as coordination (e.g, Entin & Serfati, 1999), learning (e.g., Edmondson, Bohmer, & Pisano, 2001), and conflict management (e.g., Tekleab, Quigley, & Tesluk, 2009) contribute to team outcomes, the predominant research has only take cross-sectional and linear approaches to examine the relationship between team processes and team performance, without explore the potential power of explanation that other and more flexible kind of relationships (i.e., nonlinear) can have and in coherence with the consideration of teams as complex systems. In any case, more studies which follow these phenomena over time are necessary (Mathieu et al., 2019b).

Indeed, since Marks et al. (2001) few studies have adopted a longitudinal design to examine the way change in team processes over time influences team performance, and their findings are mixed. Mathieu and Schulze (2006) tested the nature of change in team processes and performance by looking at different growth trajectories and found that linear change in team transition processes (but not team interpersonal processes) predicts team performance longitudinally. Later, Goncalo, Polman and Maslach, (2010) have found that early process conflict management (i.e., interpersonal processes) was positively associated with team performance earlier in the team performance cycle, but negatively near the task deadline. This is supported by research that shows that change in interpersonal processes over time has a positive and negative relationship with team performance, depending on how much interpersonal processes do team members engage in (Johnson, van de Choot, Delma, & Crano, 2015). Finally, another study by Costa, Passos, Bakker and Ferrão (2017) also found that extreme levels (i.e., high and low) of team interpersonal processes with a focus on team motivation building and team affect management lead to lower performance in management teams.

As mentioned earlier, while action and transition processes are expected to be positively and linearly related with team performance, interpersonal processes are expected to have a more complex relationship with team performance (i.e., nonlinear; Marks et al., 2001). Although this finds some support in the different studies mentioned in the previous paragraph, few studies have adopted an empirical approach that truly accounts for the different roles that team processes have in shaping team performance. This might be a result of the analytical techniques employed (i.e., linear approaches leading to positive vs. negative relationship between team processes and team outcomes over time), because they reduce the variability of a complex phenomenon rather than considering it as an intrinsic part of the dynamic nature of teams (McGrath & Tschan, 2004). To verify this idea, we capitalize on catastrophe modeling, one of the techniques derived from NDS, which is not constrained by such limitations (Ramos-Villagrasa et al., 2018).

Catastrophe modeling uses mathematical models of the NDS to describe discontinuous events in psychological systems (Guastello, 1987; 2001; Zeeman, 1979). The fundamental axiom of catastrophe models is Thom's (1975) classification theorem, which states that given a maximum of four control parameters, all discontinuous changes can be modeled by seven elementary topological forms, including cusp catastrophes (for a detailed review see Guastello, 2011). Fig. 1 summarizes the cusp catastrophe model of team performance.

<Insert Fig. 1 around here>

A cusp catastrophe is a three-dimensional surface that features a two-dimensional manifold (Guastello, 2011). The cusp describes one order parameter *y* that has two stable states and is a function of two control parameters: *asymmetry (a)* and *bifurcation (b).* The equilibrium plane shown in Fig. 1 regards the degree of change in the order parameter *y* for all possible combinations of the two control parameters, *b* and *a*. In the two stable (flat) regions of the equilibrium plane (A and B), change in the order parameter *y* is linear. Outside the two stable regions, when approaching the cusp region (C and D), change in the order parameter *y* becomes unstable and discontinuities take place. Catastrophic behavior happens when the values of the order parameter *y* fall within the cusp region, represented as the gray shaded, V-shaped region at center of the *asymmetry* axis.

A cusp catastrophe model of team performance should describe the abrupt transition process through which performance changes (upward and downward) or remains stable. When stable, a system will remain unaltered until it *jumps* back to its former stable state. Mathematically, team performance dynamics could be described by the following cusp catastrophe equation:

$$dy/dt = y^3 - by - \acute{a} \qquad (1)$$

Where team performance is the order parameter *y*, and team processes are the control parameters. The control parameters include one bifurcation factor *b* and one asymmetry factor *a*. The bifurcation factor *b* is responsible for the change between the two stable states (i.e., high and low team performance) of the order parameter, while the asymmetry factor *a* is responsible for the strength and discrepancy between the two stable states of the order parameter.

According to Marks et al. (2001), interpersonal processes are involved throughout performance episodes, intervening simultaneously with the transition and action processes. Through interpersonal processes team members are capable of building motivation and managing conflict during team performance episodes (Alper, Tjosvold, & Law, 2000; LePine et al., 2008; Mathieu & Shulze, 2006). Whereas meta-analytical (e.g., LePine et al., 2008) and multilevel (e.g., Killumets, D'Innocenzo, Maynard, & Mathieu, 2015) studies support a linear relationship between team interpersonal processes and team performance, the diversity of research findings describing distinct relational patterns between interpersonal processes and team performance over time suggests a nonlinear relationship between both constructs. This is also supported by Marks et al. (2001) affirmation that team interpersonal processes are sometimes good, sometimes bad for team performance. Indeed, as described earlier in this paper, empirical findings regarding the relationship between change in interpersonal processes and team performance over time are fuzzy in the sense that different studies have found that these two variables are not always related with each other (Mathieu & Schulze, 2006) and when they do their relationship is nonlinear in the sense that lower performance if more frequently observed for teams that display high and low levels of interpersonal processes (e.g., Costa et al., 2017; Goncalo et al., 2010; Johnson et al., 2015). All of this evidence suggests that interpersonal processes will be the bifurcation factor *b* in the cusp catastrophe model of team performance.

Regarding the asymmetry factor, we expect that the remaining processes (i.e., transition and action) display this role. Previous research demonstrates that both processes are positively and linearly related with how good teams perform (Marks et al., 2001; LePine et al., 2008; Marks, DeChurch, Mathieu, Panzer, & Alonso, 2005; Marks & Panzer, 2004; Mathieu & Schulze, 2006; Mathieu et al., 2019b; Ramos-Villagrasa, Passos & García-Izquierdo, 2019). Hence, we expect that the team processes will be positively related with team performance change over time, thus functioning as the asymmetry factor *a* in the cusp catastrophe model of team performance.

In this study we test two cusp catastrophe models, both with team performance as the order parameter *y* and interpersonal processes as the control parameter *b*. The first model has transition processes as the control parameter a_1, and the second one has action processes a_2 performing this role. We propose two cusp catastrophe models instead of one more complex (i.e., swallowtail catastrophe) because the theoretical model by Marks et al. (2001) considers that transition and action stages takes place in different moments: transition between performance episodes, whilst action takes place during performance episodes (LePine et al., 2008).

We anticipate that team performance *y* will become bimodal for given *b*, *a* pairs within the cusp region. This means that for a given paired value of *b* and *a* within the cusp region, two distinct values of *y* can occur (increasing performance and decreasing performance, which reflect the bimodality of *y*). Outside the bifurcation region, the distribution of the order parameter *y* becomes continuous, and any given paired values of the control parameters *b* and *a* usually produce one response type in the order parameter *y*. Since cusp catastrophes describe chaotic behavior, it can happen that for a restricted set of values of interpersonal processes *b*, very small changes in transition processes a_1 and action processes a_2 might trigger catastrophic changes in team performance. Differently, it can also happen that for other restricted set of interpersonal processes *b* values, even large changes in transition processes a_1 and action processes a_2 values might not move team performance to shift between states. Instead, such changes in the transition processes a_1 and action processes a_2 might lead to gradual and continuous change in team performance *y*. What will determine how the team performance *y* oscillates between the two stable states are the values adopted by interpersonal processes *b*, and transition processes a_1 and action processes a_2 simultaneously.

Taken the aforementioned into account, our hypotheses are as follows:

Hypothesis 1: The cusp catastrophe model of the relationship between interpersonal processes, transition processes and team performance will explain more variance than its comparable linear model.

Hypothesis 2: The cusp catastrophe model of the relationship between interpersonal processes, action processes and team performance will explain more variance than its comparable linear model.

METHOD

Participants

Participants in this study were 214 teams (N = 967). Team size ranged between 3 and 5 members (M = 4.63, SD = 0.64), 70% of the participants were men, and the average age was M = 28.64 (SD = 8.43). Fourteen percent of the participants had at least a degree in management, and 71% of the participants had never been enrolled in a previous edition of this management competition. Additionally, 42 % of the teams comprised professional workers, 42.7% comprised undergraduate students, and 15.3% were mixed.

Research Context

Data collection took place during the first national round of the 2011 Global Management Challenge (GMC), which is the world's largest and most prestigious management competition (please see The World of GMC, 2019). The use of GMC as a unique context for conducting teamwork research is not new, but it is an adequate simulation for research (e.g., Santos, Passos, Uitdewilligen, & Nubold, 2016). In the GMC, individuals form management teams that run a *virtual* company with the aim of achieving the highest investment performance, measured by the investment "return" for the original shareholders. One month before the start of the competition, participants receive all the information about the rules and the gaming environment and are assigned to two training sessions. On day 1 of the competition, the teams receive a general report that characterizes their company and the business environment where they are competing (company and market starting conditions are the same for all teams). The first national round lasts five consecutive weeks. During each week, the teams perform 66 weekly decisions related to marketing, production, personnel, purchasing, and finance. Participants take top management decisions, are given the opportunity to analyze financial and economic indicators, interact with the different functional areas of a company and are made aware of the impact their decisions have on the organization itself. As in real financial markets, the competing companies' stock auctions are sensitive to the decisions made by the company's management team. The teams always have to upload their decisions on the competition's online platform on the last day of the week, and the teams receive a weekly report informing about their company's performance and their rivals 24 hours after they submit all decisions. Every week teams receive a performance score and the winner is the team that finishes with the highest simulated share price.

Procedure

Teams were self-selected and applied together to the competition. Participants were invited to enroll in the study one month before the start of the competition. On week one of the competition, participants received the link to the online questionnaire measuring team affect and team processes after they submitted their decisions (The link was deactivated just before the performance report was made available). Team performance was regarded every week, over 5 weeks.

Measures

Table 1 presents aggregation indexes and reliability scores for team processes.

Team processes. Team processes were collected on week one of the competition using Mathieu and Marks' (2006) Team Process Taxonomy Measure, which includes 18 items equally distributed across three subscales with 6 items each. These include transition (mission analysis, goal specification, and strategy formulation and planning; an item example is "*My team established goals for this decision*"); action (coordination, monitoring progress toward goals, team monitoring and backup, and system monitoring; an item example is "My team members openly communicate amongst us"); and interpersonal (conflict management, motivating and confident building, and affect management; an item example is "My team members manage personal conflicts, adequately") processes. Participants gave their answers on a Likert type scale ranging from *totally disagree* (1) to *totally agree* (7).

Team performance. Team performance was the rank assigned to each team overall weekly decision, based on the return on investment to the respective investors by stock market capitalization and the issue or repurchase of shares and the dividends distributed. The software that runs the virtual environment of the competition automatically calculated this for each week of the competition.

Statistical analyses

Aggregation. We examined the within-group agreement index $r_{wg(j)}$ (James, Demaree, & Wolf, 1984) and the intra-class correlation coefficients ICC(1) and ICC(2) (Bliese, 2000) to decide if the aggregation of individual team members perceptions of team processes to the team level was possible. Aggregation is considered appropriate for $r_{wg(j)}$ and ICC(2) when both indices are ≥ 0.70, whereas ICC(1) values should be ≥ 0.05 and ≤ 0.20 (Bliese, 2000; James et al., 1984).

Missing data. The original sample regarded 2586 individuals (640 teams). Prior to analysis, 426 teams were removed from the data set either because they did not enroll in any of the weekly surveys or because there was only one team member responding to the surveys. Regarding the remaining 214 teams, the number of missing cases for individual responses ranged between 21% in the first week and 46.2% in the fifth week. Since all the 214 teams had at least two members responding to the surveys from at least three different weeks, we decided not to remove any. To deal with the remaining missing data, we performed Little's

(1988) test to determine if the pattern of missing data was missing completely at random (MCAR) using the missing values analysis command option in SPSS (Graham, 2009; Schlomer, Bauman, & Card, 2010). A non-significant chi-square value was obtained for missing data at the individual, $\chi^2(152) = 181.73$, $p = 0.05$, and team, $\chi^2(33) = 41.99$, $p = 0.14$, levels. This suggests that the pattern of missing data was MCAR (Little, 1988). The MCAR data pattern is not problematic because it yields parameter estimates that are close to population values (Graham, 2009).

Cusp catastrophe modeling. Nonlinear regressions (Guastello, 2011), and maximum likelihood estimation (Cobb & Watson, 1980) can be used complementarily to examine cusp catastrophe models. We adopt both methodologies since they complement each other in the analysis of nonlinear change under the cusp catastrophe theory (Ramos-Villagrasa et al., 2018). In the nonlinear regression approach, we adopted a static model for the catastrophe function since this particular model performs equally well with data that is collected on one single occasion, or on a small number (> 2) of multiple occasions over time (Guastello, 2011). The cusp analysis for team performance was the probability density function of the cusp response surface, expressed by the nonlinear regression function described in the equation 2:

$$Pdf(z) = \xi exp\left(\theta_1 z_1^4 + \theta_2 z_1^3 + \theta_3 b z_1^2 + \theta_4 a\right) \tag{2}$$

Where θ_i and ξ are nonlinear regression weights, with ξ being a proportionality constant that does not impact on the elements of the cusp that appear within parentheses. *Pdf(z)* is the cumulative probability of the order parameter, z (as y) is the order parameter, b is the bifurcation factor, and a is the asymmetry factor. The parameters z, b and a have been corrected for location and scale. The arguments with the exponents describe the potential function for the cusp, with regression weights and a cubic term. When fitting the cusp model, optimal fit is reached when all four nonlinear regression parameters are statistically significant. In the current study, we tested two cusp catastrophe models using equations 3 and

4, which describes the cusp catastrophe model of team performance ($Pdf(z)$) with interpersonal processes ($\theta_3 IPz_1^2$) as the bifurcation factor and transition processes ($\theta_4 TP\, z_1$) and action processes ($\theta_4 AP\, z_1$) as the asymmetry factors.

$$Pdf(z) = \xi exp\left(\theta_1 z_1^4 + \theta_2 z_1^3 + \theta_3 IPz_1^2 + \theta_4 TP_2 z_1\right) \quad (3)$$

$$Pdf(z) = \xi exp\left(\theta_1 z_1^4 + \theta_2 z_1^3 + \theta_3 IPz_1^2 + \theta_4 AP_2 z_1\right) \quad (4)$$

If all the parameters obtain statistical significance, or at least the quartic ($\theta_1 z_1^4$) and bifurcation ($\theta_3 IPz_1^2$) parameters do, it can be assumed that all the local dynamics of the model are true (Guastello, 2011).

Additional calculations were performed using the maximum likelihood estimation (Cobb & Watson, 1980), which allows for more flexibility in the definition of the role that each parameter will play in the cusp catastrophe model. It also allows researchers to test for cusp catastrophe models with multiple bifurcation and asymmetry factors simultaneously (Grasman, van der Maas, & Wagenmakers, 2009). The major disadvantage over the direct estimation method is that the indirect estimation method is more demanding since it includes more parameters during the estimation process (Guastello, 2011). Through the maximum likelihood approach, the statistical significance of the cusp model is determined by the values of the pseudo-R^2 of the cusp model and the logistic model, compared against the R^2 of the linear regression model. Since the pseudo-R^2 is not a trustworthy guide in selecting the best model, it should be regarded with additional model fit indexes that guide the assessment of model fit (Grasman et al., 2009). These are the Akaike's criterion (AIC), Akaike's criterion corrected for small samples (AIC_c), and Bayes information criteria (BIC) indexes. The estimation of the cusp model following the maximum likelihood estimation procedure is done using R package "cusp" (Grasman et al., 2009).

RESULTS

Aggregation Indexes and Descriptive Statistics

The results presented in Table 1 show the aggregation and reliability statistics for the control (i.e. team processes) and order (i.e. team performance) parameters. Following James et al. (1984) and Bliese (2000), the average $r_{wg(j)}$ and the ICC(1) indexes of the control parameters were within standards, while the ICC(2) index was below the recommended threshold of .70. Bliese (2000) argues that small ICC(2) values are not any impediment to data aggregation because lower ICC(2) values only attenuate the strength of the relationship between variables. Therefore, we proceeded with the aggregation of data by averaging individual team members' responses.

The results presented in Table 2 generally suggest that team processes correlated positively with team performance.

<Insert Table 1around here>

<Insert Table 2 around here>

Hypotheses Testing

Following recommendations by Gilmore (1993) and Grasman et al. (2009), as a first step towards hypotheses testing we have looked for the existence of catastrophe flags that signal the existence of chaotic behavior in the order parameter *y* (Gilmore, 1993), namely the bimodality of team performance at different levels of the bifurcation variable *b*. To this aim, we have computed 4 histograms of team performance over time, for different levels of team interpersonal processes. The histograms in Fig. 2 suggest that team performance becomes bimodal at extreme levels of interpersonal processes, thus preliminary supporting the presence of a cusp catastrophe and the role of interpersonal processes as a bifurcation factor.

<Insert Fig. 2 around here>

The overall R^2 of the cusp model for team performance using nonlinear regression (Guastello, 2011) was $R^2_{\text{Cusp}} = 1.00$, F (5, 1065) = 14539400.00, $p < .001$. Regarding hypotheses testing, the results of the cusp models for team performance ($Pdf(z)$) with interpersonal processes ($\theta_3 IPz_1^2$) as the bifurcation factor and transition processes, ($\theta_4 TP\, z_1$), $R^2_{\text{Cusp}} = .93$, F (5, 1065) = 16889.06, $p < .001$, and action processes ($\theta_4 AP\, z_1$), $R^2_{\text{Cusp}} = .93$, F (5, 1065) = 16889.82, $p < .001$, as the asymmetry factors outperformed the two linear models ($R^2_{\text{Linear}} = .01$; $R^2_{\text{Linear interaction}} = .02$). The results in Table 3 and Table 4 also suggest that lower levels of interpersonal processes and higher levels of transition processes and action processes contribute to the discontinuity of the cusp response surface in a negative way (i.e., team performance moves from the C to D region in the cusp control plane, in Fig. 1 and Fig. 4). These results support hypotheses 1 and 2.

The results of the cusp model of team performance using maximum likelihood (Cobb & Watson, 1980) also adds additional information regarding the role of team processes in shaping team performance dynamics over time. Following Cobb and Watson (1980), as well as Grasman et al. (2009), the estimation of cusp catastrophe models using maximum likelihood recommends that all the order and control parameters defining the cusp model are included from the start. Depending on the significance levels achieved by the control parameters, one can remove those that do not achieve statistical significance.

In this study, we begun by defining a cusp catastrophe model where transition, action and interpersonal processes were simultaneously bifurcation and asymmetry factors. Different from what we had hypothesized, the results displayed in Table 5 suggest that transition processes function as a bifurcation factor, B = .42, $SE = .16$, $Z = 2.26$, $p = .01$, 95% CI [0.101; 0.100], while interpersonal processes function as an asymmetry factor, B = .26, $SE = .09$, $Z = 2.78$, $p = .001$, 95% CI [0.077; 0.443]. Action processes did not play any significant role in the cusp model. Additionally, as with the nonlinear regression estimation (Guastello, 2011), the cusp model of team performance using maximum likelihood (Cobb & Watson, 1980) explained more variance in the data (R^2 = .68) than the linear regression (R^2 = .05) and the logistic regression models (R^2 =.07). The χ^2 difference test between the linear and cusp models, as well as the model fit statistics provided by the AIC, AICc, and BIC indexes supported these findings. The results displayed in Table 4 show that higher levels of transition and interpersonal processes contribute to the discontinuity of the cusp response surface in a positive way (i.e., team performance moves from the D to C region in the cusp control plane, in Fig. 1 and Fig. 4).

Using both the nonlinear regression and the maximum likelihood methodologies has enabled us to describe the nonlinear dynamics of team performance over five weeks (see Figs. 3 and 4).

<Insert Fig. 3 around here>

<Insert Fig. 4 around here>

DISCUSSION

The current research has built on the NDS theory (Guastello & Liebovitch, 2009), the theory of small groups as CAS (Arrow et al., 2000) and the taxonomy of team processes (Marks et al., 2001) to test the general assumption that change in team performance over time can be described by means of nonlinear modeling (i.e. cusp catastrophe models). Furthermore, the current study also tested the general hypothesis that change in team processes over time determines linear and nonlinear changes in team performance.

In line with previous research (e.g., Ramos-Villagrasa et al., 2012), the results suggest that team performance follows nonlinear patterns over time. This finding strengthens the view of teams as CAS (Arrow et al., 2000) by showing that team performance change over time is characterized by abrupt, rather than smooth, dynamics. Nonetheless, our findings are also mixed in the sense that they suggests that transition processes and interpersonal processes can both contribute to the continuous and discontinuous changes in team performance over time. While in the nonlinear regression model, lower performance is triggered when transition processes are the asymmetry factor and interpersonal processes are the bifurcation factor, in the maximum likelihood whereas higher performance is triggered when transition processes are the bifurcation factor and interpersonal processes are the asymmetry factor.

As Marks et al. (2001) and Hackman (2012) suggest, the clearer the roles, goals and strategy shared by team members across tasks, missions and projects, the smoother and more positively they will perform. Needs to make new arrangements in team functioning will be less and disruptions in team performance due to conflict, role uncertainty or loss of direction will be unlikely. The research findings regarding team interpersonal processes were also in line with our research hypothesis, although they were new in the sense that in this particularly study interpersonal processes were theorized to trigger abrupt shifts in team performance over time. Whereas Marks et al. (2001) acknowledged this possibility, to the best of our knowledge the results of the current study provide the first empirical evidence that such assumption is true. Team interpersonal processes are team, rather than task oriented, creating the conditions for transition and action processes to smoothly leverage team performance. However, when teams devote little time to interpersonal processes, this might imply that team members are not attending fundamental group behaviors such as regulating affect and motivation or managing the conflict that emerges from group interactions during problem solving and decision making. Similarly, when team members highly engage in confidence building or spend many hours working around conflicts, the group might deviate their focus from the tasks and performance may drop (Mathieu et al., 2019b). Assuming that a minimum amount of conflict, affect and motivation is desirable to trigger optimal performance, average levels of interpersonal processes should lead to better team outcomes than extreme values (Arrow et al., 2000; Costa et al., 2017).

Regarding action processes, these are the main predictors of team performance (LePine et al., 2008; Mathieu et al., 2019b). On this regard, our research findings were mixed. They suggest that while action processes alone contribute to linear change (i.e., proportional) in team performance, when they are regarded with transition processes simultaneously their relationship with team performance becomes non-significant. This would suggest that transition processes alone contribute to explain most of the linear change in team performance over time.

All in all, in line with the work Hackman (2012), our results reiterate the idea that what teams do (i.e., transition processes) before they engage in team task activities has greater implications for how they perform over time than what they actually do during the performance cycle (i.e., action processes). Furthermore, our findings are also in line with Fleishman's Leadership Theory (e.g., Fleishman & Simmons, 1970) and the idea that effective leaders engage in in consideration and structure behaviors, which are proxies to transition and interpersonal processes in teams.

Research Implications

The theory of teams as CAS (Arrow, et al., 2000), alongside the taxonomy of team processes (Marks et al., 2001) and Hackman's (2012) view of enabling conditions to team effectiveness all regard teamwork as complex process, characterized by sensitiveness to initial conditions, emergence and discontinuities. The outcomes of this research contribute to strengthen dynamics views of teamwork by showing that (a) the temporal dynamics of team performance follow nonlinear patterns (e.g., Guastello & Guastello, 1998; Ramos-Villagrasa et al., 2012) and (b) the value of adopting analytical methodologies from within the NDS realm to further expand our knowledge of team performance. The adoption of cusp catastrophe modeling in the present study also contributes to a more holistic view of the role that team processes have as antecedents of team performance, providing empirical support to Marks et al. (2001) idea that how team processes change over time and relate with team performance is neither an additive or continuous process, but rather a discontinuous one. Finally, our research findings strengthen previous research showing a linear and positive relationship between transition processes, action processes and team performance (e.g., Mathieu et al., 2019b), as well as clarifies previous findings showing sometimes mix results regarding the role of interpersonal processes (e.g., Johnson et al., 2015). Through this research we helped disentangling how interpersonal processes contribute to explain upward and downward jumps in team performance across a performance cycle.

The outcomes of our research also contribute to a better informed practice of team work because they suggest that the extent to which team members engage in interpersonal processes can trigger positive and negative jumps in team performance over time. Hence, team members and team leaders should be mindful of the impact that their attempts to build team positive affect or increase team members' motivations to accomplish collective goals is having (or may have) in team performance. Another contribution regards the possibility that transition processes, rather than action processes, greatly determine the performance outcomes of teams enrolled in short duration processes. This is somehow in line with Hackman (2012) views that the conditions that teams set prior to the start of their tasks, or earlier in their performance cycle greatly determine how they will perform over time and the extent to which they will have to make many adjustments to how they work.

Research limitations and future directions

The current research has several limitations that cannot go unnoticed. First, the nature (i.e., simulation) and specificity (i.e., management teams) of the research context suggest caution in generalizing our research findings. Nevertheless, the adoption of management simulations, such as the one used in this study, is not new in I/O Psychology and OB research (e.g., Guastello & Guastello, 1998; Santos et al., 2015). The closeness between simulation and reality increases the likelihood that participants will behave in a similar way to how they would behave when performing in real environments. This strengthens the reliability and generalizability of the research findings.

A second limitation in our study is that participating teams are not real teams, which prevents us to be sure that the results we have found in our study fully replicate those in the real teams. Therefore, an interesting extension of our research would be replicating our findings in a naturalistic setting, also using samples that include new comers' teams and tenured workers' teams.

Third, teams were performing in a *competitive* work environment, and performance comparisons were possible at the end of every week. The fact that the teams could compare their performances may have also influenced how the teams behaved. Nevertheless, the competitiveness of the management simulation in which the participants were enrolled renders greater ecological validity to our research because most real-world business environments are competitive by nature, and companies constantly benchmark their rivals searching for opportunities to improve performance.

A fourth limitation in this study was missing data. Missing data often raises several concerns regarding research findings reliability. However, the fact that the pattern of missing data in this study was MCAR, and given the utilization of FIML to test our hypotheses, the chance that missing data had an effect on the research outcomes is very small (Graham, 2009).

Finally, the different team processes examined in this research are deemed to occur at different moments of the team performance (Marks et al., 2001). One interesting extension of our research would be to conduct additional research that allows the modeling of causality relationship over time among these three processes simultaneously.

CONCLUSION

Twenty years ago, Arrow and colleagues formally introduced the theory of small groups as CAS. Illuminating as it was in the years that followed there were few contributions that validated it as a unifying theory binding the teamwork literature together (Hackman, 2012; Ramos-Villagrasa et al., 2018). It is remarkable that the majority of research finding suggest that change in team processes over time is related with change in team performance but little research yet exists that can help us to fully understand their temporal dynamics. The outcomes of the current study offer empirical support to Marks et al.'s (2001) and Arrow et al. (2001) by showing that team performance dynamics are nonlinear and that team processes determine smooth, as well as discontinuous change in the performance of teams.

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Table 1. Aggregation indexes and reliability

	$r_{wg(j)}$				ANOVA	ICC 1	ICC2	α
	M	Median	Min.	Max.				
1. Transition processes $_{t1}$	.84	.91	-0.58	1.00	1.42**	.08	.29	.89
2. Transition processes $_{t2}$	.86	.92	-0.84	1.00	1.83**	.15	.45	.92
3. Transition processes $_{t3}$	.72	.88	-2.13	1.00	1.40**	.08	.28	.95
4. Transition processes $_{t4}$	.84	.91	-0.63	1.00	1.96**	.17	.49	.95
5. Transition processes $_{t5}$	.78	.91	-2.13	1.00	2.08**	.19	.52	.97
6. Action processes $_{t1}$	.86	.91	0.00	1.00	1.38**	.08	.27	.89
7. Action processes $_{t2}$	.85	.91	-1.02	1.00	1.75**	.14	.43	.93
8. Action processes $_{t3}$	.64	.88	-2.78	1.00	1.33**	.07	.25	.97
9. Action processes $_{t4}$	.84	.93	-0.73	1.00	1.96**	.17	.49	.96
10. Action processes $_{t5}$	.78	.91	-2.13	1.00	2.09**	.20	.18	.97
11. Interpersonal processes $_{t1}$	.87	.94	0.21	1.00	1.48**	.09	.32	.94
12. Interpersonal processes $_{t2}$	.84	.94	-1.02	1.00	1.80**	.15	.44	.96
13. Interpersonal processes $_{t3}$	.81	.92	-0.47	1.00	1.66**	.12	.40	.97
14. Interpersonal processes $_{t4}$	.83	.92	-0.60	1.00	1.91**	.16	.48	.97
15. Interpersonal processes $_{t5}$	.78	.88	-2.13	1.00	1.89**	.16	.47	.98

Note. N = 967 (valid listwise = 647); t stands for time.

Table 2. Correlations and descriptive statistics.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	*M*	*SD*
1. TP $_{t1}$.	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	5.61	.49
2. TP $_{t2}$.	.49	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	5.74	.53
3. TP $_{t3}$.	.36	.52	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	5.53	.58
4. TP $_{t4}$.	.46	.51	.51	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	5.67	.55
5. TP $_{t5}$.	.29	.36	.38	.49	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	5.68	.59
6. AP $_{t1}$.	.64	.44	.43	.47	.37	1	-	-	-	-	-	-	-	-	-	-	-	-	-	5.84	.42
7. AP $_{t2}$.	.54	.72	.56	.55	.43	.62	1	-	-	-	-	-	-	-	-	-	-	-	-	5.82	.48
8. AP $_{t3}$.	.24	.40	.84	.47	.39	.44	.53	1	-	-	-	-	-	-	-	-	-	-	-	5.61	.59
9. AP $_{t4}$.	.45	.55	.65	.82	.61	.53	.66	.63	1	-	-	-	-	-	-	-	-	-	-	5.76	.49
10. AP $_{t5}$.	.29	.38	.46	.57	.83	.46	.51	.50	.72	1		-	-	-	-	-	-	-	-	5.70	.54
11. IP $_{t1}$.	.49	.34	.39	.39	.31	.73	.61	.40	.46	.38	1		-	-	-	-	-	-	-	6.30	.41
12. IP $_{t2}$.	.42	.65	.51	.49	.38	.51	.85	.49	.60	.45	.50	1	-	-	-	-	-	-	-	6.09	.50
13. IP $_{t3}$.	.34	.54	.61	.58	.49	.50	.66	.71	.74	.58	.51	.69	1	-	-	-	-	-	-	5.99	.53
14. IP $_{t4}$.	.39	.48	.63	.67	.48	.48	.60	.63	.87	.60	.48	.60	.78	1	-	-	-	-	-	5.93	.50
15. IP $_{t5}$.	.26	.40	.49	.57	.72	.42	.53	.52	.72	.90	.41	.52.	.65	.70	1	-	-	-	-	5.89	.54
16. P $_{t1}$.	.12	.31	.23	.24	.11	.14	.28	.19	.22	.19	.11	.26	.22	.21	.23	1	-	-	-	4.99	2.28
17. P $_{t2}$.	.16	.19	.22	.32	.13	.15	.25	.21	.24	.20	.19	.16	.24	.24	.25	.61	1	-	-	4.97	2.29
18. P $_{t3}$.	.18	.19	.13	.30	.14	.14	.17	.144	.29	.24	.16	.19	.23	.30	.27	.43	.55	1	-	5.17	2.20
19. P $_{t4}$.	.20	.24	.23	.35	.18	.15	.20	.23	.32	.29	.20	.19	.32	.35	.36	.44	.58	.77	1	5.18	2.23
20. P $_{t5}$.	.21	.18	.23	.24	.21	.15	.18	.21	24	.22	.16	.19	.26	.30	.30	.35	.49	.68	.75	5.20	2.21

Note. N = 214. Grey correlation scores are not statistically significant for $p > .05$. All other correlations are statistically significant for $p < .05$. t stands for "time". TP regards transition processes. AP regards action processes. IP regards interpersonal processes. P regards performance.

Table 3. Results of the cusp model for transition processes, interpersonal processes and performance with Nonlinear Regression estimation.

			95% CI		
Model	R^2	β	Lower limit	Upper limit	Model *F*
Team performance					
Linear model	.05				29.62**
Interpersonal processes		.15	0.336	0.972	
Transition processes		.10	0.124	0.719	
Linear interaction	.05				19.92**
Interpersonal processes		.16	0.360	1.036	
Transition processes		.11	0.129	0.725	
Interaction		.03	-0.061	0.135	
Cusp model	.93				16889.06**
Team performance ($\theta_1 z^4$)		-392.27	-412.641	-371.916	
Cubic term ($\theta_2 z^3$)		159.29	151.257	167.331	
Interpersonal processes ($\theta_3 bz^2$)		-2.32	-3.643	-0.991	
Transition processes ($\theta_4 az$)		1.52	1.194	1.848	

Note. †$p < .06$ *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (two-tailed).

Table 4. Results of the cusp model for action processes, interpersonal processes and performance with Nonlinear Regression estimation.

			95% CI		
Model	R^2	β	Lower limit	Upper limit	Model *F*
Team performance					
Linear model	.05				27.11**
Interpersonal processes		.15	0.204	1.053	
Action processes		0.09	-0.053	0.806	
Linear interaction	.05				18.12**
Interpersonal processes		.14	0.158	1.046	
Action processes		0.09	-0.054	0.806	
Interaction		-.014	-0.109	0.071	
Cusp model	.93				16889.82**
Team performance ($\theta_1 z^4$)		-398.92	-418.601	-379.174	
Cubic term ($\theta_2 z^3$)		164.58	156.978	172.174	
Interpersonal processes ($\theta_3 bz^2$)		-4.82	-6.470	-3.161	
Action processes ($\theta_4 az$)		2.04	1.609	2.468	

Note. †$p < .06$ *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (two-tailed).

Table 5. Results of the cusp model for team performance with Maximum Likelihood estimation.

Model	B	*S.E*	Z-value		95%CI Lower Limit	Upper Limit
Cusp						
Intercept (*y*)	-2.17	.06	-37.17	< .001	-2.280	-2.051
Team performance (*y*)	.48	.01	48.82	< .001	0.474	0.513
Intercept (*b*)	.62	.72	0.87	.385	-.783	2.029
Transition processes (*b*)	.42	.16	2.58	.010	0.101	0.741
Action processes (*b*)	-.43	.22	-1.87	.061	-0.881	0.019
Interpersonal processes (*b*)	.15	.06	.83	.408	-0.205	0.505
Intercept (*a*)	-2.31	.37	-6.19	< .001	-3.037	-1.577
Transition processes (*a*)	.13	.08	1.52	.129	-0.037	0.294
Action processes (*a*)	.05	.12	.44	.660	-0.181	0.285
Interpersonal processes (*a*)	.26	.09	2.78	.001	0.077	0.443
Model fit statistics	R^2		AIC	AICc		BIC
Linear regression model	.05		4713.405	4713.462		4738.282
Logistic regression model	.07		4699.999	4700.169		4744.778
Cusp catastrophe model	.68		2673.681	2673.889		2723.435
χ^2 difference test between the Linear model and the Cusp model						2050 (5) p = 0

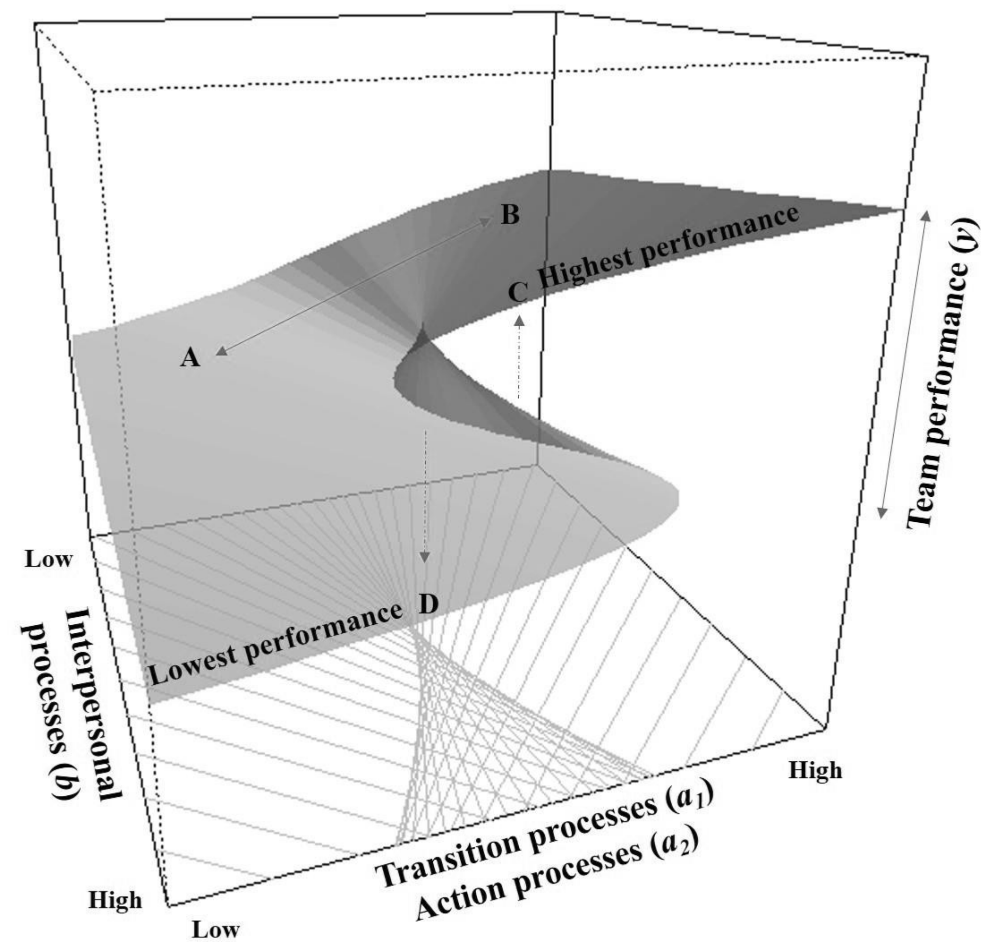

Fig. 1. Cusp catastrophe model of team performance, with interpersonal processes as the bifurcation factor and transition and action processes as the asymmetry factors.

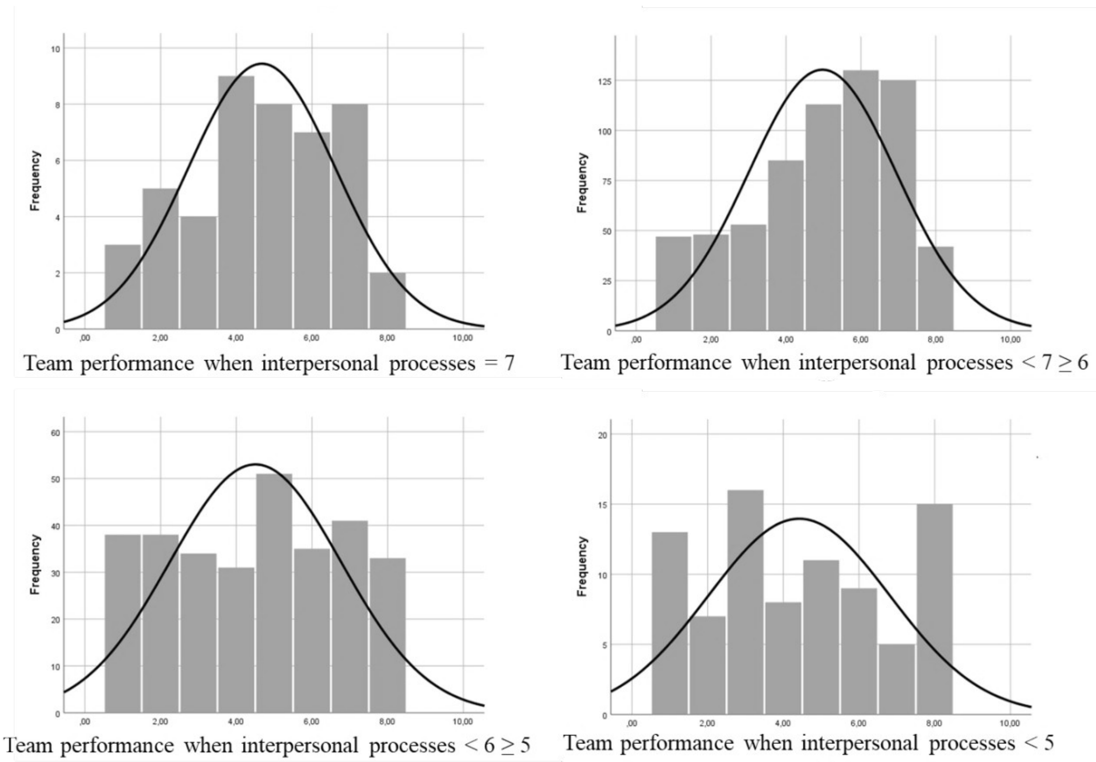

Fig. 2*.* Histograms with normal curve distribution for team performance at different values of the hypothesized bifurcation factor (team interpersonal processes).

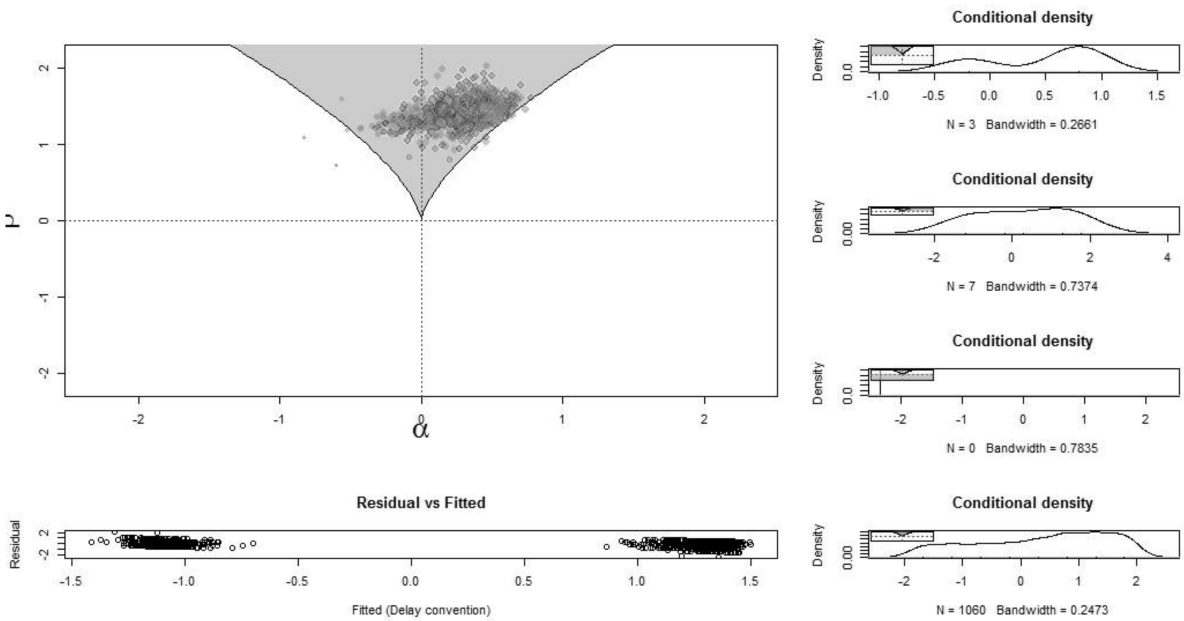

Fig. 3. 2-Dimension cusp *pdf* for team performance using the Maximum Likelihood estimation. Dots represent observed values of team performance for each team over five weeks.

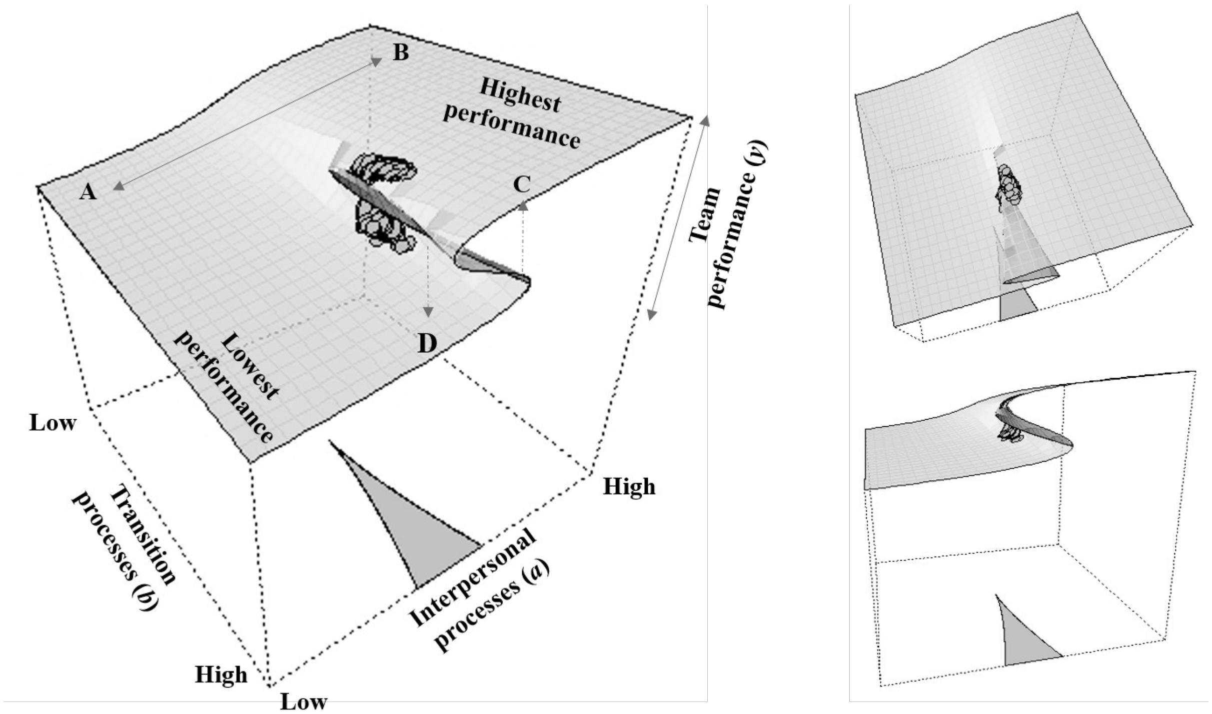

Fig. 4. 3-Dimension cusp *pdf* for team performance using the Maximum Likelihood estimation. Team transition processes are the bifurcation factor and team interpersonal processes are the asymmetry factor. Grey dots represent observed values of team performance for each team over five weeks.