

Title

Chaotic [dynamics and](#) team effectiveness: evidence from professional basketball

Short title

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Authors

Ramos-Villagrasa, Pedro J. (Department of Psychology, University of Oviedo, Spain)

Navarro, José (Department of Social Psychology, University of Barcelona, Spain)

García-Izquierdo, Antonio L. (Department of Psychology, University of Oviedo, Spain)

Correspondence

Pedro José Ramos Villagrasa

Facultad de Psicología, cabina nº5, Plaza Feijóo s/n, 33003 Oviedo (Spain)

E-mail: ramospedro@uniovi.es

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Abstract

Considering teams as complex adaptive systems (CAS) this study deals with changes in team effectiveness over time in a specific context: professional basketball. The sample comprised 23 basketball teams whose outcomes were analysed over a twelve-year period according to two objective measures. The results reveal that all the teams showed chaotic dynamics, one of the key characteristics of CAS. A relationship was also found between teams showing low-dimensional chaotic dynamics and better outcomes, supporting the idea of healthy variability in organizational behaviour. The stability of the squad was likewise found to influence team outcomes, although it was not associated with the chaotic dynamics in team effectiveness. It is concluded that studying teams as CAS enables fluctuations in team effectiveness to be explained, and that the techniques derived from nonlinear dynamical systems, developed specifically for the study of CAS, are useful for this purpose.

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This paper focuses on the temporal dynamics of team effectiveness in a specific work context: professional basketball teams. The premise is that seemingly random patterns of team effectiveness over time could actually reveal discernible trends. As such the study is of interest not only for team psychology research, which has emphasized the need to consider teams as complex systems (e.g. Arrow, McGrath & Berdahl, 2000), but also for the applied perspective, since it provides information about the possibility of predicting and intervening in team effectiveness.

Team effectiveness and teams as complex adaptive systems (CAS)

Teams can be defined as a set of two or more people with specific roles who interact dynamically, interdependently and adaptively toward a common objective (Salas, Dickinson, Converse & Tannenbaum, 1992). In this study the focus is on effectiveness, the core of team research as it reflects the results of a team's actions (Kozlowski & Bell, 2003).

Surprisingly there is no consensus regarding the definition of team effectiveness. Although Campbell, McCloy, Oppler and Sager (1993) clarified many years ago that performance refers to behaviour itself while effectiveness is an outcome of performance, team effectiveness is nowadays considered alternatively as behaviour (i.e. performance) and in terms of outcomes (Mathieu, Maynard, Rapp & Gilson, 2008). Here, we follow the proposal of Salas, Rosen Burke and Goodwin (2009), who have defined team effectiveness as an evaluation of the results of performance in accordance with certain standards.

The explanation and prediction of effectiveness is a key question in the field of team research. As noted by Ilgen, Hollenbeck, Johnson and Jundt (2005), and more recently by Mathieu et al. (2008), various models based on the input-process-output (I-P-O) framework of McGrath (1964) have been developed in an attempt to explain team

effectiveness. However, these models have been criticized for ignoring the dynamic nature and temporal evolution of teams (Ilgen et al., 2005; Mathieu et al., 2008; McGrath, Arrow & Berdahl, 2000). Consideration of the temporal aspect may therefore provide new insights and enable researchers to ask questions that can only be answered with a dynamic approach (Ancona, Goodman, Lawrence & Tushman, 2001; Arrow, Poole, Henry, Wheelan & Moreland, 2004). For example, Mitchell and James (2001) show that a causal relationship between two variables can be affected by time in five different ways, with the number of such possibilities growing as more variables are added. Research that takes account of time is also useful for practitioners as it allows phenomena to be monitored from the moment they begin. By identifying critical changes in trajectories the practitioner may then be able to prevent unfavourable turns in them, thereby avoiding negative consequences (Roe, 2008).

Current explanatory models of team effectiveness have begun to include time and consider teams as complex, adaptive and dynamical systems (e.g. Arrow et al., 2000; Ilgen et al., 2005; Mathieu et al., 2008). A complex adaptive system (CAS) can be defined as a set of independent agents that act in parallel, develop models of how things function in their setting and, most importantly, refine these models through learning and adaptation (Gell-Mann, 1994). According to McGrath et al. (2000) and Arrow et al. (2004), conceptualizing teams as CAS implies that teams interact with other systems, some smaller (i.e. the members of the team), some of the same size (i.e. other teams) and others larger (i.e. the organizations in which the teams find themselves and their context). These authors also argue that team research has shown a number of serious limitations, such as considering teams as simple systems characterized by unidirectional cause-effect relationships, failing to take into account the context in which teams operate, and studying them as static entities that do not change over time

and which are comprised of generic individuals who can be exchanged without consequence (McGrath et al., 2000). One way of overcoming these limitations would be to consider teams as CAS.

In addition to the above, Ilgen et al. (2005) point out that empirical research about teams is more problem-driven than theory-driven (i.e. the changing demands of the applied setting have constrained empirical research, with few studies being conducted on the development and testing of theories). One example is the construct of CAS itself: many authors talk about teams as CAS, but very little research has actually sought to demonstrate this.

According to McGrath (1991) the way to study teams as CAS is through nonlinear dynamical systems (NDS) theory, which is specifically designed for this purpose (Lewin, 1993). NDS theory considers CAS as a development of open systems that show an evolution over time, one in which their components interact in a nonlinear and dynamical way (Guastello & Liebovitch, 2009). From the perspective of NDS theory the characteristics of CAS are interdependence, interaction, uncertainty and chaos (Nowak & Vallacher, 1998). Interdependence occurs when team members need not only to cooperate to achieve shared goals (Cummings & Blumberg, 1987) but also to take into account how external factors influence the team (Kozlowski & Bell, 2003). Interaction is intrinsically related to interdependence, because teams need to be related to their context in order to perform their task in a mixed-motive situation, as suggested by studies about cooperation and competition (Stewart & Nandkeolyar, 2007). Uncertainty refers to the lack of surety about the results of team effectiveness due to within-team dynamics and context interdependence. Last but not least, chaos refers to a type of temporal dynamics that characterizes certain processes which appear to behave stochastically (i.e. they are apparently non-deterministic) when in fact their

development is determined by rules and is predictable to some degree. Following Lorenz (1993) we can distinguish three main characteristics of chaos: 1) sensitive dependence (i.e. the possibility of establishing a predictive horizon but not a complete prediction of the future evolution of chaotic phenomena); 2) fluctuations in dynamics are deterministic, not random; and 3) fluctuations describe non-overlapping trajectories through time.

Chaos has a central role in the empirical study of CAS. Given the dynamical nature of CAS, NDS theory approaches their study by means of time series (Heath, 2000). A time series is a collection of sequential observations made over time (Chatfield, 1996), and within these sequences certain patterns can be found. Following Nowak and Vallacher (1998) time series patterns can be classified according to their predictive capacity (see Figure 1). As we can see, a distinction can be made between deterministic (i.e. predictable) and non-deterministic (i.e. non-predictable) patterns. Deterministic patterns can be further divided into linear patterns, which maintain cause-effect proportionality, and nonlinear ones, which do not. The most frequent nonlinear pattern is the chaotic one, i.e. a phenomenon pattern that is characterized by chaos. Moreover, chaotic patterns can be low-dimensional or high-dimensional (Mathews, White & Long, 1999), a distinction which refers to the number of variables that adequately determine the pattern (few or many). Additionally, low-dimensional chaos is much more orderly than high-dimensional chaos (Kauffman, 1993). This means that low-dimensional chaos can fluctuate a lot, but the rules which determine these fluctuations are discernible and predictions can be made, at least in the short term. By contrast, in high-dimensional chaotic series many values are possible, the fluctuations are greater and sudden changes occur very often, which makes any kind of prediction quite difficult.

[INSERT FIGURE 1 HERE]

Although near-linear patterns can be studied using the techniques developed under the assumptions of the generalized linear model (such as ARIMA models), the study of non-linear patterns requires specific techniques that are rarely used in psychology (e.g. visual recurrence analysis, phase space maps, etc.; Guastello & Liebovitch, 2009). This is especially true for the analysis of chaotic patterns, where chaos and randomness could be confounded when using linear models (Heath, 2000). However, NDS techniques are able to determine whether a time series is deterministic or not. If it is deterministic, one can then identify the kind of deterministic pattern (linear, low-dimensional chaos or high-dimensional chaos) and, therefore, the most suitable method for analysing the data (Ramos-Villagrasa & García-Izquierdo, 2011).

Given that teams are now widely considered as CAS, and taking into account the growing research that shows how NDS theory can be applied to team dynamics (e.g. Gorman, Amazeen & Cooke, 2010; Pincus, Fox, Perez, Turner & McGeehan, 2008; Wheelan & Williams, 2003), our goal here is to analyse patterns of team effectiveness across time and to determine whether or not they are chaotic. Specifically, we seek to provide empirical evidence that can help to clarify whether it is indeed appropriate to conceptualize teams as CAS. Furthermore, we would like to contribute knowledge about the effects of time on teams, this being a question that remains largely unexplored to date (Conroy, Kaye & Schantz, 2008). If, as expected, teams are CAS and their effectiveness shows chaotic patterns, it will then be necessary to conduct more in-depth research into their dynamics (e.g. monitoring, predicting, optimizing) so as to obtain new insights and, consequently, to propose ways of intervening in teams (Roe, 2008).

The present study

The aim of this study was to analyse team effectiveness over time. Specifically, we sought to determine if there were chaotic patterns in the behaviour of a sample of Spanish professional basketball teams and, secondly, if there was some kind of dynamical pattern associated with the achievement of better team outcomes.

Team research in sport settings offers certain advantages to researchers. Following Browne and Mahoney (1984) and Loy, McPherson and Kenyon (1978) these advantages are: a) research is conducted mainly in the natural context; b) the rules, organizational systems and hierarchy of sport enable a better analysis and control of variables; c) the activity usually develops under zero-sum circumstances, enabling the analysis of cooperation, competition and conflict between teams; and d) objective measures of effectiveness are available, thereby allowing a longitudinal approach.

The sport studied here, basketball, is described by Barnes and Morgeson (2007) as follows: “At any given time, only 5 members are actively participating in the competition, though other team members may be substituted in at any time [...]. Each team has the opportunity to attempt to both score points (i.e., accumulate points for their team by having the player put the ball through a hoop) and prevent the other team from scoring points” (p. 266). In line with Landis (2001), García-Izquierdo, Ramos-Villagrasa and Navarro (in press), and Wolfe et al. (2005) we consider basketball as an organizational setting. Sports teams are a part of organizations (Carron & Brawley, 2008) in which the same processes and behaviours occur as in the case of conventional work organizations (Dirks, 2000). Additionally, professional players are employees of their sports clubs and have job duties that are set out in law (in Spain, Law on Sport 10/1990, art. 46).

Like other sports teams, basketball teams have been considered as CAS (Davids, Araújo & Shuttleworth, 2005; García-Izquierdo et al., in press). As regards the

abovementioned characteristics of CAS, i.e. interdependence, uncertainty, interaction and chaos (Nowak & Vallacher, 1998), at least three are present in the basketball setting: high task interdependence (Landis, 2001), high interaction, and uncertainty, as a consequence of the interaction between team members and their context (Wall, Cordery & Clegg, 2002). In other words, basketball teams are *task-interdependent* because they cannot play a match without there being *interaction* between players and the context (i.e. the other team, the spectators, and so on), and *uncertainty* is high because in every match the composition of each team changes several times and the final outcome also depends on the rival team's performance; the circumstances may also change from one match to another.

Regarding *chaos*, García-Izquierdo et al. (in press) have shown that more than 80% of professional basketball players reveal chaotic dynamics in their individual outcomes, but to the best of our knowledge no one has yet studied the effectiveness dynamics of basketball teams. Indeed, very little research has been conducted into the chaotic nature of team effectiveness, although the empirical evidence suggests that team sports such as indoor football and water polo do show typical chaotic dynamics (e.g. Davids, Vilar, Travassos & Araújo, 2010; Passos et al., 2011). Given the conceptualization of CAS and the empirical evidence derived from other sports, it therefore seems reasonable to expect that basketball teams will show chaotic patterns in their outcomes. Thus, our first hypothesis is:

H₁: The patterns of team effectiveness in professional basketball teams will be mostly chaotic in nature, as opposed to other types of patterns.

Additionally, and inspired by the work of Bak and Chen (1991), we are interested in identifying which chaotic pattern (i.e. low-dimensional or high-dimensional) is the most frequent. The empirical evidence suggests that low-

dimensional chaos (i.e. deterministic and predictable to some degree) is more frequent than high-dimensional chaos (i.e. deterministic but unpredictable and near to random) in organizational settings. For instance, Cheng and Van de Ven (1996) studied the innovation processes in a biomedical context by analysing three time series: decisions made by innovation teams, the results obtained by these teams, and the number of contextual events relevant to the innovation processes. Their results revealed low-dimensional chaos in decisions and results, but a random pattern in contextual events. For their part Navarro and Arrieta (2010) used a diary method to examine the work motivation of 48 workers, and found that 42 of them (87.5%) showed a low-dimensional pattern. Finally, Richards (1999) studied the dynamics of three different decision-making processes, one in an experimental context and two in the real context. Both the real-context series had low-dimensional chaotic patterns.

Given their preponderance in organizational settings we would also expect to find patterns of low-dimensional chaos in the present study of basketball teams. As such, our second hypothesis is:

H₂: The chaotic patterns found in the team effectiveness of professional basketball teams will be mostly of the low-dimensional kind.

In the context of professional sports it is common practice to change some squad members each season in order to improve team results and introduce innovations in playing style (Montanari, Silvestre & Gallo, 2008). The empirical evidence suggests that squad changes do improve team effectiveness provided a certain degree of stability is guaranteed (e.g. Arrow & McGrath, 1995; Berman, Down & Hill, 2002; Montanari et al., 2008), i.e. a core group of players is retained from one season to another. These changes may influence the dynamics of team outcomes, and one might postulate that team stability would generate fewer fluctuations in outcomes (i.e. they will tend to

display linear or low-dimensional chaotic patterns, but not high-dimensional or random ones). As such, the third hypothesis is sub-divided into two:

H_{3a}: The stability of the squad will be positively associated with team effectiveness.

H_{3b}: Teams with more stability in their squads will tend to show more predictable patterns of team effectiveness (linear or low-dimensional chaos).

A final aim of the study is to understand the relevance of chaotic dynamics for team effectiveness. Research in the field of psychophysiology has demonstrated that low-dimensional chaotic patterns are associated with healthy outcomes, while linear patterns ([and the absence of any pattern as well, i.e. random dynamic](#)) are linked to malfunctions (e.g. Freeman, 1991; Goldberger, 1991; Kaplan et al., 1991). This phenomenon, termed *healthy variability* by Ceja and Navarro (2011), has also been reported in the context of organisational psychology, where low-dimensional chaos has been shown to be associated with better results in work motivation (Arrieta, Navarro & Vicente, 2008), flow experiences (Ceja & Navarro, 2011) and teams (Guastello, 2010). The work of Guastello (2010), for instance, shows that the more effective emergency response teams exhibit indicators of low-dimensional chaotic patterns.

Generalizing these results to the team sports context, one would expect to find healthy variability in our study. Basketball teams that respond flexibly and creatively to the uncertainty of their environment, changing their behaviour ~~so~~ as to adapt continuously and to evolve with the environment, should achieve better outcomes. One of the reasons for this is that the wide variety of behaviours displayed by CAS makes them capable of adapting to changing and unpredictable environments. Applied to the present study the healthy variability phenomenon would mean that a team showing low-dimensional chaotic patterns would obtain better outcomes (e.g. better results, reaching

play-offs, etc.) than would teams with other patterns. Thus, our final hypothesis is as follows:

H₄: Teams with low-dimensional chaotic patterns in their effectiveness tend to obtain better results at the end of the competition than do those teams with other patterns.

Method

Participants

The study sample comprised teams from the Spanish Premier Basketball League (known as the ACB), in which eighteen teams participate each year. As in other European competitions the teams with the worst end-of-season results are relegated to a lower league (Wolfe et al., 2005). In this regard, a prerequisite for inclusion in the sample was that a team had played for at least three consecutive seasons in the league during the twelve-year observation period (1996 – 2008), thus ensuring a sufficient number of recordings for a time-series analysis from the perspective of NDS theory (Heath, 2000). Twenty-three of the 29 possible teams (79.31%) that made up the sample pool fulfilled this condition and were entered into the analyses, with the remainder being excluded. The data were gathered between January and June 2009 from the league's official website.

Measures

Two effectiveness ~~measures time series~~ were ~~used by~~ ~~measured using~~ robust time series based on team outcomes recorded during every match by trained observers. Team statistics and the results of each match were published on the league's official website, from where the research team gathered these data. In accordance with the classification

of Guzzo and Dickson (1996) the two measures used referred to group-produced outputs.

The first measure was a composite criterion established by the league and which includes various positive and negative results that a team achieves in every match. This criterion captures the behavioural outcomes of the team (shots, rebounds, turnovers, etc.), is referred to as Statistics ('S') and is calculated via the following formula:

$$S = (a + b + c + d + e + f) - (w + x + y + z)$$

where a is the number of points per game, b is the number of rebounds obtained per game, c is the number of assists per game, d is the number of steals per game, e is the number of personal fouls committed by the other team per game, f is the number of blocked shots per game, w is the number of missed shots per game, x is the number of turnovers per game, y is the number of rebounds failed per game, and z is the number of personal fouls committed per game.

The second measure of team effectiveness was the position of each team in the league at the end of each day's play ('Ranking'). This position varies according to the number of matches won by the team, and in the event that two teams have won the same number of matches, the ranking is decided by the number of points scored and conceded during the season. The best rankings are represented by the lowest values (i.e. 1 for first, 2 for second, and so on).

We also measured the teams' end-of-season results by the number of play-offs ('Play-offs') for the title of champion in which they were involved during the observation period (12 years). The play-offs are the final phase of the competition, and only eight teams qualify for this each season. Being able to reach a play-off position at the end of the league is seen as a sign of success by all teams.

Finally, team stability was measured by the mean proportion of players in the squad who remained from one season to another. This piece of data was also recorded for teams that were relegated and later returned to the Premier League.

All these measures are objective, thereby avoiding the problems associated with perceptual measures (Humphrey, Morgeson & Mannor, 2010). Moreover, the use of robust time series (i.e. with hundreds of records) reduces the likelihood of committing Type I and Type II errors when establishing relationships between variables in research involving time (see McGrath, Arrow, Gruenfeld, Hollingshead & O'Connor, 1993).

Procedure and analysis

The first step involved conducting a descriptive analysis of the time series (Statistics and Ranking) for the participating teams. Then, in order to test hypotheses 1 and 2, the patterns were analysed by means of three complementary techniques which have been developed within the framework of NDS theory: maximal Lyapunov exponent, recurrence plot and surrogate data. As stated above, techniques derived from NDS theory are used because they enable us not only to identify patterns that other techniques do not (i.e. linear and near-to-linear ones), but also to differentiate between chaotic and random patterns, a critical distinction in contexts involving dynamic systems such as teams. All the analyses were performed using specific software: Chaos Data Analyzer (Sprott & Rowlands, 1995) for the maximal Lyapunov exponent, Visual Recurrence Analysis 4.8 (Kononov, 2005) for the recurrence plots, and TISEAN 3.0 (Hegger, Kantz & Schreiber, 2007) for surrogate data. Given that these techniques have not been widely used in research on teams they are briefly described below. A more detailed review can be found in Heath (2000).

Lyapunov exponents indicate the rate of divergence of two initially-close trajectories in phase space. Phase space is a geometric representation in which the

values adopted by the variable over time are the coordinates of an m -dimensional space (where m is the number of variables necessary to describe the behaviour of a system, also called the embedding dimension). If the rate of divergence is greater than zero then the series is regarded as chaotic, whereas a value of zero or less indicates that the series is linear. If all we are interested in knowing is the time series pattern then we only need to calculate the maximal Lyapunov exponent, since a single positive exponent is sufficient for a series to be considered as chaotic (Heath, 2000). However, it is advisable to use this measure in combination with other statistics because the maximal Lyapunov exponent is not adequate for distinguishing between random and chaotic cases.

The recurrence plot can be used as a complement to the results derived from Lyapunov exponents. A recurrence plot is a graph that calculates the proximity of points on a two-dimensional graph containing all the possible trajectories of the time series, distinguishing between deterministic series (both linear and chaotic) and non-deterministic series (i.e. random; Heath, 2000). Its main limitation is that the identification of the pattern represented by the recurrence plot always depends on the interpretations made by the researcher. This is especially problematic when it comes to differentiating between random and high-dimensional chaotic patterns. However, one way of resolving any discrepancies between the maximal Lyapunov exponent and the recurrence plot is to use surrogate data.

Surrogate data are used to rule out the possibility that the time series pattern is due to chance, in other words, the possibility that although the values of the series are distributed in this way it is equally likely that they could have been distributed in any other way. The logic behind the surrogate data procedure is simple: random series are generated from the original series and a rank-order test is then performed in order to rule out the possibility that the original series is also random (Theiler, Eubank, Longtin,

Galdrikian & Farmer, 1992). If previous analyses (Lyapunov exponents and recurrence plot) have identified a given series as random but the surrogate data rule out this possibility, then the series in question is considered to show high-dimensional chaos. If all the analyses (Lyapunov exponents, recurrence plot and surrogate data) produce congruent results (e.g. they all indicate chaotic behaviour) the series is considered to show low-dimensional chaos.

In order to test hypothesis 3_a we analysed the correlations between the stability of each team and its effectiveness. The association between variables was established by means of Spearman correlations, which do not require the assumption of normality to be fulfilled. Lastly, ANOVA was used to test hypotheses 3_b and 4.

Results

Table 1 shows information regarding the teams that made up the sample, along with the results of the descriptive analysis of the time series used in the present study. It can be seen that the squad size ranged between 11 and 15, and squad stability between 28.85% and 58.69%. The number of play-offs contested by the teams varied between 0 and 12. As regards the size of the time series these ranged between 102 and 408 points, which is sufficient for the analyses performed (Heath, 2000). As expected, teams with better mean statistics have longer time series (more years in the Premier League), whereas those with poorer statistics tend to get relegated and have shorter time series. The mean value for the Statistics measure ranged between 71.27 and 92.05. As regards the Ranking, this is an ordinal variable and it was therefore analysed using the median (whose values ranged between 2 and 17) and the mode (values between 1 and 18). It is also worth noting that all the teams occupied the first and eighteenth league positions at one time or another.

[INSERT TABLE 1 HERE]

The next step involved identifying the pattern of each time series. Table 2 shows the results broken down by effectiveness measure (Statistics and Ranking), while Figure 2 provides examples of results derived from each technique for each pattern (linear, low-dimensional chaos, high-dimensional chaos and random). It can be seen that all the teams show chaotic patterns in their effectiveness, thus confirming the first study hypothesis. Because neither linear nor random patterns were found in the sample, Figure 2 also includes, for illustrative purposes, an example of each of these dynamics. As regards the second hypothesis it was expected that chaotic patterns would be low-dimensional for both measures (Statistics and Ranking), but the results show that this was only the case with respect to Statistics, specifically in 65.22% of cases. Therefore, the second hypothesis is only partially supported.

[INSERT TABLE 2 HERE]

[INSERT FIGURE 2 ABOUT HERE]

Hypothesis 3_a was tested by obtaining the correlations between the mean squad stability and team effectiveness. As can be seen in Table 3 the Spearman correlations reveal a strong association between team stability and Statistics ($r_s = .83, p < .01$), Ranking ($r_s = -.81, p < .01$) and the number of play-offs contested ($r_s = .88, p < .01$). These results therefore support hypothesis 3_a.

[INSERT TABLE 3 HERE]

With respect to hypothesis 3_b we tested for the presence of a relationship between team stability and the patterns found in team effectiveness. As our sample is small, Durbin-Watson, Kolmogorov-Smirnov and Levene's tests were first applied to

analyse independence, normality and homoscedasticity, respectively, prior to performing the ANOVA. The results showed that homoscedasticity was not supported in the case of Ranking. Welch's test was therefore used instead of the F test in the analyses regarding Ranking. As all the cases were identified as chaotic by the surrogate data analysis, the differences were examined by considering the type of chaos, i.e. distinguishing between time series according to whether they showed low- or high-dimensional chaos. We then compared team effectiveness with the stability of the series, but as Table 4 shows there were no significant differences between the teams with respect to either Statistics ($F=0.62, p<.44$) or Ranking (Welch= $1.64, p<.22$). Given that squad stability was not related to patterns in team effectiveness, hypothesis 3_b was not supported.

[INSERT TABLE 4 HERE]

The final study hypothesis was related to the phenomenon of healthy variability. This was tested by using ANOVA to analyse the association between the observed patterns and the number of play-offs contested. As before, we tested for independence, normality and homoscedasticity, and as the same results were obtained Welch's test was again used for Ranking. The ANOVA results are shown in Table 5, where it can be seen that the relationship was significant in the case of Statistics ($F= 5.68, p<.03$). Additionally, and as illustrated in Figure 3, teams with low-dimensional chaotic patterns were involved in more play-offs ($M=5.67$) than were teams with high-dimensional chaotic patterns ($M=1.38$). Therefore, the fourth hypothesis is partially confirmed.

[INSERT TABLE 5 HERE]

[INSERT FIGURE 3 HERE]

Discussion and Conclusions

This paper reports the analysis of two objective measures of team effectiveness in 23 professional basketball teams over a period of twelve seasons (12 years). The aim was to identify any chaotic patterns characteristic of CAS, and to determine whether any pattern was associated with better team outcomes. As noted above, teams have been considered as CAS by various authors, but few studies to date have provided empirical evidence that teams show a defining characteristic of CAS (e.g. Gorman et al., 2010; Pincus et al., 2008; Wheelan & Williams, 2003) and, to the best of our knowledge, there is no research of this kind in relation to professional basketball. The main findings of this study were as follows: 1) all the teams showed a deterministic pattern; 2) this deterministic pattern was chaotic; 3) the pattern was not related to team stability; and 4) teams with low-dimensional chaotic patterns achieved better results at the end of the season. Let us consider each of these findings in more detail.

Pattern identification is basic to NDS theory because it reveals any noteworthy consistency in the phenomenon under study (in this case, team effectiveness). Consequently, it shows that prediction is possible despite apparent irregularity (see time plots in Figure 2). This occurs because CAS tend to display changes that result from intrinsic dynamics, although external variables may also produce changes in them (Guastello & Liebovich, 2009; Nowak & Vallacher, 1998). As Nowak and Vallacher (1998, p. 33) state, “the causal effects of external variables are difficult to describe without taking into account the system’s internally generated sources of change. In attempting to model and predict change, then, it is necessary to consider the interaction of both external and internal forces.” Our data are consistent with this assertion: when team effectiveness is measured by Ranking, characterized by high external influence (the results of all matches are taken into account), it is less predictable than when

measured by the Statistics measure, which depends solely on the effectiveness of the team and its rival.

The predictive capacity of a given team depends on whether its effectiveness is characterized by low- or high-dimensional chaos. This aspect must clearly be taken into account in professional practice, in which decisions are frequently based on the most recent results, even though this would only be valid if the team shows a linear or near-linear pattern. In our view it would be advisable, when making decisions, to begin by identifying and analysing the pattern so as to determine the type of fluctuations shown by the team in the past, before considering this information alongside current results.

The study also examined the stability of teams. The literature suggests that squad changes can lead to better results provided a certain degree of stability is ensured, although research into effectiveness patterns over time is scarce. On the basis of the present results it can be concluded that stability is related to team effectiveness (i.e. greater stability leads to greater effectiveness), although surprisingly the patterns found in team effectiveness are not attributable to team stability (i.e. greater stability is not related to the pattern shown). One possible explanation for this result, which was unexpected, is provided by findings in other team contexts (e.g. Gorman et al., 2010; Guastello, Bock, Caldwell & Bond, 2005; Weick & Gilfillan, 1971). For example, Guastello et al. (2005) found that team coordination (see Weick & Gilfillan, 1971) persisted after changing up to two members of a four-person group; the original study by Weick and Gilfillan (1971) showed that effectiveness patterns persisted in a group after everyone had sequentially changed. More recently, Gorman et al. (2010) analysed the dynamics in intact vs. mixed teams across time, reporting that mixed teams (i.e. teams with changes to their members) were more stable but also more adaptive. In the sports context Montanari et al. (2008) found that team stability had a positive impact on

effectiveness up to a critical point, after which it might be detrimental. Our results are consistent with this literature. Indeed, a possible explanation for our results is that patterns are intrinsic to the team and its collective, dynamic and changing nature (McGrath et al., 2000), regardless of team stability (Guastello et al., 2005; Weick & Gilfillan, 1971). Obviously, these results and their corresponding explanation, founded on NDS theory and its proposal regarding intrinsic dynamics, must be tested with further research. Nonetheless, the findings have both theoretical and practical relevance. Specifically, we suggest that introducing a few squad changes, even when a team's evolution over time is unknown (i.e. in the case of high-dimensional chaotic patterns) could increase effectiveness by making the team more adaptive.

Another noteworthy finding was that teams with low-dimensional chaotic patterns in Statistics had better results at the end of the season. In addition to providing further evidence of healthy variability (Ceja & Navarro, 2011) this raises the question as to which variables predict the type of pattern that a team will show. This aspect should be addressed in future research as it would enable the formation of more effective teams. The variables proposed as being predictive of team effectiveness by dynamic models, such as those based on the IMOI framework (Ilgen et al., 2005; Mathieu et al., 2008), would be a good starting point for research into this question. These models conceptualize teams as CAS whose outputs influence the organizational system, contextual contingencies, and environmental dynamics and complexity, which, in turn, influence the inputs, thereby generating a cyclical and reciprocal process (Kozlowski & Ilgen, 2006).

A further finding of note is that no association was found between the pattern of the Ranking measure and teams that were involved in more play-offs. This could be due to the fact that whereas the Statistics measure depends mainly on the team and its most

immediate context (the opposing team), a team's ranking is also influenced by the behaviour of other teams, which would explain the increased presence of high-dimensional chaotic patterns (i.e. a higher number of variables is necessary to explain Ranking dynamics).

Given the above, we suggest that coaches need to acknowledge the inherent instability in teams, avoiding attempts to control the team and trying, by contrast, to manage uncertainty. In other words, they should embrace the instability that is inherent in teams and use it to their benefit. As stated by Zimmerman, Lindberg and Plsek (2001) this implies: managing teams through flexible criteria that can be modified according to the situation; encouraging a variety of opinions so as to foster innovation and adaptation; creating the right conditions for facing challenges; establishing guidelines that are not so specific that they cannot be altered; taking into account informal relationships; and promoting cooperation and competition at the same time. The research by Bourbousson, Poizat, Saury and Seve (2011) is an example of how this kind of management can be applied to the sports context. According to these authors, shared knowledge of the team promotes effectiveness, but this shared knowledge changes during the course of a match. Consequently, coaches must teach team members to use the opportunities for coordination as they appear in a match, thereby updating the shared knowledge of the team.

Finally, the study has demonstrated the appropriateness of the chosen statistical methods and techniques for studying teams as CAS, this being an aspect which other authors had previously recommended (Mack, Huddleson, Dutler & Mintah, 2000; Mathieu et al., 2008; McGrath, 1997). The advantage of these techniques is that they focus on whether the series are deterministic or not, but without presupposing a given data structure. Thus, they can be used as a form of screening, after which the

appropriate analytical technique (linear or nonlinear) can be applied (Ramos-Villagrasa & García-Izquierdo, 2011).

Limitations and recommendations for future research

The present study does have certain limitations. Firstly, although conducting the research in the context of professional basketball makes it easier to replicate, caution should be exercised when extrapolating the results. For example, it may be that the particular features of basketball, such as the relationships between team components and the need for high-level effectiveness in a competitive setting, lead to the emergence of chaotic patterns. Another example is the low stability of the squad compared with other organizational settings. In longitudinal sports research a team's name remains the same yet its composition may change drastically (Montanari et al., 2008). This turnover does not mean that sports teams cannot be studied, but it is an aspect that must be considered in the future. Further research should therefore aim to determine the degree to which the present results can be generalized to other similar teams and contexts. Other teams to which these results might generalize must share at least the three characteristics that we stated above: interdependence between team members, uncertainty about the future, and a close interaction between the team and its immediate context.

A second limitation of the study is the possible effect of range restriction due to the uniqueness of the sample. The study has focused on the highest level of competition in Spain, where both teams and players are more homogeneous than at lower levels due to the entry requirements and the standard of results and resources required in order to participate, etc. This circumstance could have influenced the results. It would therefore be advisable to conduct similar studies at other competitive levels which are characterized by greater diversity.

A third limitation concerns the measures used in the study. The use of archival data has both critics and supporters. Critics such as Campbell et al. (1993) argue that objective measures are influenced by context and that they are related to results rather than to behaviour. Conversely, authors such as Landis (2001) and Stewart and Nandkeolyar (2007) consider that such measures show consistency and objectivity. In our view, both objective and subjective measures are useful, and which kind is used will depend on the purpose of the study (Muckler & Seven, 1992). In this regard, we believe that our measures of effectiveness are consistent with our objectives.

Lastly, the number of teams studied here is too low to rule out any effect of methodological artefacts (e.g. low statistical power in correlations) on the results, and hence more research is needed to provide additional support. Furthermore, the techniques used do not test if the time series are affected by seasonality, i.e. periodic fluctuations derived from context (e.g. the beginning or the end of the league). Further research about the potential presence and influence of seasonality in relation to basketball time series is therefore required. Nonetheless, we believe that our research is valuable as an important step towards understanding how professional basketball teams might be conceptualized as CAS, even if the conclusions should be regarded as preliminary.

[As regards Continuing with](#) recommendations for future research there is a need to determine which variables predict the patterns of team effectiveness. To this end the potential of the NDS framework should be explored in greater depth so as to develop predictive short-term models that explain a high proportion of variance with a few variables (Mathews et al., 1999). An especially interesting example of these applications is the work of Keil and Cortina (2001), who performed a meta-analysis about the temporal consistency of cognitive ability and its relationship to performance at the

individual level, showing that the methodology based on NDS theory provides a new and promising perspective.

In terms of predictive capacity, and as already stated, one can distinguish what is known as low-dimensional chaos, which can be described with a few variables and in which short-term predictions are possible. One avenue for further research would therefore be to use dynamical and nonlinear models of prediction to investigate which variables are key when it comes to explaining the greater amount of variance. In this regard it would also be interesting to analyse how team effectiveness emerges out of the individual effectiveness of team members, as Arrow et al. (2004) and García-Izquierdo et al. (in press) have suggested. One could tentatively assume that teams will tend to show more complex patterns than would their members, due to the interaction and interdependence of the latter, and this would generate emergent processes (e.g. cohesion or shared mental models) and results that act as feedback. As such, team effectiveness would appear as showing new properties that cannot be reduced to individuals, but which nonetheless remains predictable, at least in most cases.

Conclusion

The present study continues a line of research conducted over the last two decades which has shown that in order to understand group behaviour it is necessary to consider teams as complex, adaptive and dynamical systems. This paper brings the question to the professional sports context, where effects of time have been largely unexplored. Having provided new empirical evidence in support of the conceptualization of teams as CAS the next step is to determine precisely how this can be used to improve team effectiveness. Our study has four key findings: firstly, team effectiveness fluctuates considerably; secondly, it is possible to find discernible trends in team effectiveness; thirdly, these trends are not related to stability of the squad; and

lastly, a low-dimensional chaotic pattern is related to better team results. Further research using the longitudinal, dynamical and nonlinear approach of the NDS framework will add greater depth to these findings, increasing our knowledge about team effectiveness and about teams themselves.

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Table 1

Squad, team results and descriptive statistics of the time series

Team	Size of the squad	Mean stability of the squad	Number of play-offs	Time series size	Statistics				
					M	SD	Min.	Max.	Mdn
A	13	44.65%	2	204	78.73	19.81	35	135	14
B	14	56.34%	12	408	90.94	19.58	39	151	3
C	15	34.87%	1	136	76.93	18.14	23	117	12
D	13	34.44%	0	238	74.67	19.53	23	140	13
E	12	33.36%	0	238	77.14	19.38	29	128	13
F	13	28.85%	0	170	72.67	19.83	17	133	16
G	13	58.69%	10	408	85.57	20.22	25	143	7
H	12	38.38%	3	340	76.49	19.98	10	128	11
I	11	29.30%	0	102	71.27	21.99	17	122	17
J	13	40.74%	4	408	82.16	20.07	17	154	11
K	13	44.83%	6	408	79.15	19.37	16	135	8

Table 1 (continued)

Squad, team results and descriptive statistics of the time series

Team	Size of the squad	Mean stability of the squad	Number of play-offs	Time series size	Statistics				
					M	SD	Min.	Max.	Mdn
L	14	35.23%	0	306	78.27	18.69	33	149	14
M	14	48.22%	8	408	88.42	18.98	42	156	8
N	13	29.12%	1	170	73.71	20.38	33	123	14
O	14	37.10%	1	136	80.49	18.56	29	129	13
P	12	42.00%	2	306	80.66	18.95	20	132	11
Q	12	32.13%	0	102	73.98	17.78	32	125	16
R	14	49.41%	9	408	89.14	18.95	33	151	2
S	14	40.87%	12	408	79.28	17.85	17	124	10
T	14	38.26%	2	408	92.05	20.79	13	167	4
U	13	45.60%	11	408	83.50	20.33	31	146	7

Table 1 (continued)

Squad, team results and descriptive statistics of the time series

<i>Team</i>	<i>Size of the squad</i>	<i>Mean stability of the squad</i>	<i>Number of play-offs</i>	<i>Time series size</i>	<i>Statistics</i>				<i>Ranking</i>			
					<i>M</i>	<i>SD</i>	<i>Min.</i>	<i>Max.</i>	<i>Mdn</i>	<i>Mode</i>	<i>Min.</i>	<i>Max.</i>
V	14	46.06%	11	408	85.16	19.75	28	139	6	5	1	18
W	12	37.80%	1	408	77.90	19.39	24	138	13	16	1	18

Note. $N = 23$. The names of the teams have been replaced by a letter to avoid their identification.

Table 2

Patterns of team effectiveness

	<i>Statistics</i>	<i>Ranking</i>
Step 1. Maximal Lyapunov exponent		
Linear patterns	0 (0.00%)	0 (0.00%)
Chaotic patterns	23 (100.00%)	23 (100.00%)
Step 2. Recurrence plot		
Linear patterns	0 (0.00%)	0 (0.00%)
Low-dimensional chaotic patterns	15 (65.22%)	7 (30.43%)
High-dimensional chaotic patterns or random patterns	8 (34.78%)	16 (69.57%)
Step 3. Surrogate data (final results)		
Linear patterns	0 (0.00%)	0 (0.00%)
Low-dimensional chaotic patterns	15 (65.22%)	7 (30.43%)
High-dimensional chaotic patterns	8 (34.78%)	16 (69.57%)
Random patterns	0 (0.00%)	0 (0.00%)

Note. $N = 23$.

Table 3

Spearman correlations

	1	2	3	4
1. Statistics	1			
2. Ranking	-.87**	1		
3. Number of play-offs	.76**	-.84**	1	
4. Team stability	.83**	-.81**	.	1
			88**	

Note. $N = 23$.

** = $p \leq .01$, one-tailed.

Table 4

ANOVA between team effectiveness and team stability

Statistics	Sum of Squares	Degrees of freedom	<i>F</i>	Sig. <i>F</i>
Inter-groups	45.81	1	.62	.44
Intra-groups	1552.72	21		
Total	1598.53	22		
Ranking	Sum of Squares	Degrees of freedom	<i>Welch</i>	Sig. <i>F</i>
Inter-groups	106.92	1	1.64	.22
Intra-groups	1491.60	21		
Total	1598.52	22		

Note. *N* = 23.

Table 5

ANOVA between team effectiveness patterns and number of play-offs contested

Statistics	Sum of Squares	Degrees of freedom	<i>F</i>	Sig. <i>F</i>
Inter-groups	96.10	1	5.68*	.03
Intra-groups	355.20	21		
Total	451.30	22		

Ranking	Sum of Squares	Degrees of freedom	<i>Welch</i>	Sig. <i>F</i>
Inter-groups	.65	1	.03	.86
Intra-groups	450.65	21		
Total	451.30	22		

Note. *N* = 23.

* \leq .05

Figure 1

Classification of time series according to their predictive capacity

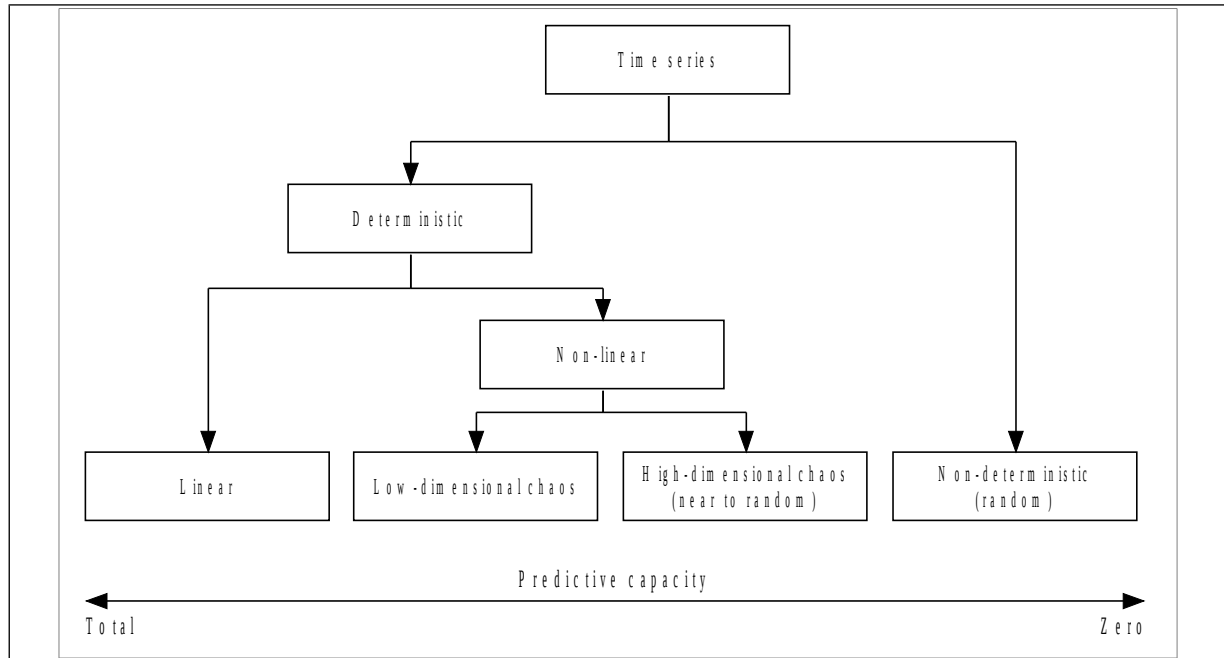


Figure 2

Sample cases of linear, low-dimensional chaos, high-dimensional chaos and random patterns

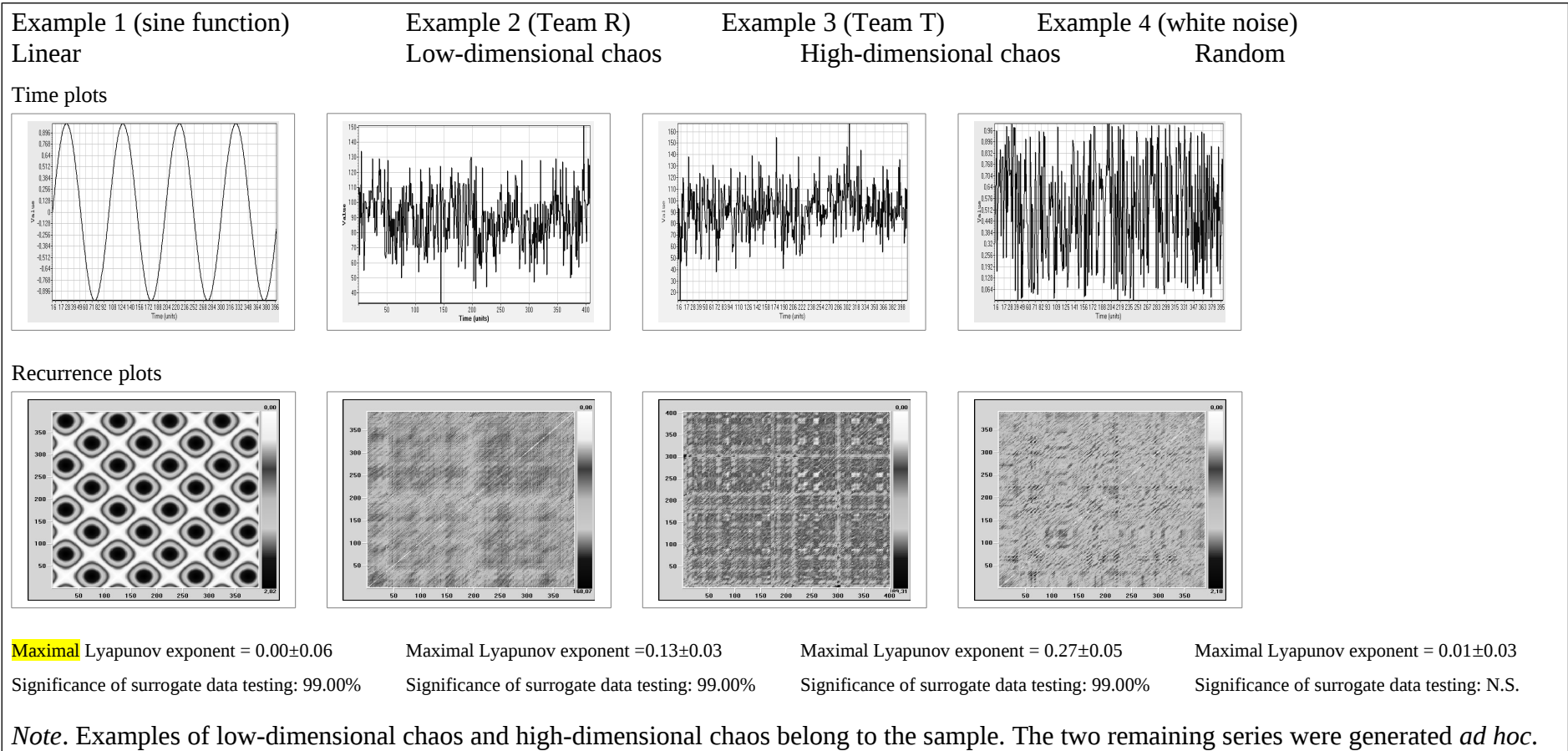


Figure 3

Mean differences between low-dimensional chaotic patterns and high-dimensional chaotic patterns with respect to the number of play-offs contested

