FLOW AT WORK

Measurement and Implications

Edited by Clive Fullagar and Antonella Delle Fave
Redefining Flow at Work

Lucia Ceja and Jose Navarro

Freeman Dyson, a renowned theoretical physicist, describes the process of entering flow as a sort of struggle:

I have to always force myself to write, and also to work harder at a science problem. You have to put blood, sweat, and tears into it first. And it is awfully hard to get started. I think most writers have this problem. I mean, it’s part of the business. You may work very hard for a week producing the first page. That’s really blood, tears, and sweat, and there is nothing else to describe it. You have to force yourself to push and push with the hope that something good will come out. And you have to go through that process before it really starts to flow easily, and without that preliminary forcing and pushing probably nothing would ever happen. So, I think that is what distinguishes it from just having a good time. You really enjoy the activity once you are really in the flowing phase, but you have to overcome some sort of a barrier to get there.

(Csikszentmihalyi, 1997, p. 117)

It is this same struggle that employees face in their everyday experience at work, as they must be continually responding to motivational forces, such as entropy or equilibrium, and instability or the enjoyment that comes from confronting new challenges. The force of entropy is more primitive and tends to be stronger. This force gives employees pleasure when they are comfortable, when they can relax, when they can get away with feeling good without expending energy (Csikszentmihalyi, 1997). Entropy leads the employee to a zone of stable equilibrium. If employees did not have this space of equilibrium or built-in regulator, they could easily become burned out and would lack the necessary strength to develop their daily work activities.
Nevertheless, employees have also the urge to master new challenges and stretch their skills to the utmost (Csikszentmihalyi, 1997). This force leads employees into a zone of expansive instability, such as the “flowing” zone described by Freeman Dyson. Without this expansive force, employees would remain in the “equilibrium” zone, where they tend to repeat work-related activities the same way they have done it in the past. The expansive force leads employees to experience flow and therefore high levels of creativity (Csikszentmihalyi, 1996), performance (Demerouti, 2006), and well-being (Fullagar & Kelloway, 2009). Work-related flow can be defined as a sudden moment where everything “just clicks,” or a state of being in the zone, when affective and cognitive modes are perfectly synchronized, giving rise to employees’ greatest performances and personal bests (Csikszentmihalyi, 1990).

Work-related flow is a developmental and dynamic phenomenon that undergoes continuous changes over time (Rathunde & Csikszentmihalyi, 2006). Every flow experience contributes to the growth of the self (Delle Fave, Massimini, & Bassi, 2011; Massimini & Delle Fave, 2000). After every episode of flow, employees are a little different from what they were before. Their consciousness contains fresh information about the new skills they have developed – for instance in the foregoing example, Freeman Dyson, after passing the barrier of entropy and facing the challenge of solving a science problem, is likely to go away with a proud knowledge that he has finally gained a better understanding of his subject of study. To continue providing optimal experiences, flow activities must be constantly recreated and Freeman Dyson’s struggle to find flow emerges every time employees visualize new opportunities for action.

Csikszentmihalyi (1990) states that disequilibrium between challenges and skills is inevitable and needs to be continually addressed by the employee. In other words, coping with work events unfolds dynamically over time, so the same work activity may be a source of distress or positive challenge at different times. In the simplest terms, an employee transforms boredom into flow by finding new challenges and overcomes anxiety by building on new skills. This process proceeds in the direction of greater complexity, creating highly unstable realities.

The definition of flow has changed very little since Csikszentmihalyi’s original formulation in 1975, and there is strong agreement among researchers on the definition itself. At the same time the models of flow, in conjunction with its measurement methods, are changing, and modifications of the flow theory are starting to emerge (Moneta, 2012). In this sense, when work-related flow is studied longitudinally over short periods of time (e.g., days, weeks, and months), it presents continuous fluctuations and changes (Fullagar & Kelloway, 2009). Likewise, several studies have found that flow at work tends to behave in a nonlinear manner (e.g., Ceja & Navarro, 2011; Guastello, Johnson, & Rieke, 1999). Ergo, a new mind-set for understanding work-related flow has started to emerge; this new mind-set considers nonlinearity and discontinuous change that employees experience in their everyday struggle of transitioning between a nonflow state (e.g., boredom or anxiety) and the flow state.

The present chapter aims to contribute to the development of this new mind-set for understanding work-related flow as a highly dynamic process, by integrating
Redefining flow at work

83

In our view, new approaches to study flow that consider its dynamic nature are necessary for at least two reasons. First, although research on work-related flow has focused on intra-individual variation, most research is based on methods that focus on variation between subjects. There is growing evidence that developmental processes, such as flow, are nonergodic processes, which are better studied using person-specific dynamic models (Molenaar & Campbell, 2009). Second, findings from physiology, psychology, and management have shown that certain properties of nonlinear systems, notably chaotic dynamics and catastrophic changes, are indicative of health, innovation, and creativity. Hence it becomes relevant to understand the dynamic nature of chaos to understand the behavior of optimal experiences at work, such as flow.

Overall, the present chapter will describe how the integration of NDS theory with the study of flow can represent an important step for understanding optimal experience at work, as a nonequilibrium condition where abrupt and discontinuous changes naturally emerge. Similarly, this enriched conceptualization of work-related flow can have important implications for organizational practice. For instance, managers can increase optimal experience at work by designing interventions according to a nonlinear model of work-related flow. We will organize the chapter as follows. We will start off by outlining why flow can be considered as a nonergodic process and therefore it is important to study the intra-individual variation of flow using person-specific dynamic models. Next, we will give an overview of NDS theory and potential applications to questions in work-related flow, and the relevance of NDS methods for developing person-specific dynamic models. Finally, we will discuss the implications that this nonlinear conceptualization has for research and organizational practice.

Flow as a nonergodic process

Although the value of flow at work is being actively explored and scholars have provided valuable insights regarding its main components, research has mainly been focused on variation between people (Ceja & Navarro, 2012). The overreliance on interindividual variation is not unique to work-related flow scholarship; rather, it is common to most research areas in psychology (Molenaar, 2004; Molenaar & Campbell, 2009; Roe, 2013).

Interindividual variation is used to derive statistics (e.g., means, correlations) that characterize the state of affairs in the population of subjects. In other words, the statistics concerned are obtained by pooling across people; this is a key hallmark of interindividual variation. Nowadays in psychology most statistical methods are centered on the analysis of interindividual variation, regardless of whether the data are collected cross-sectionally, longitudinally, or using multilevel designs (Molenaar & Campbell, 2009). It seems natural and reasonable to infer that conclusions about the state of affairs at the population level can imply general findings that apply to each individual person in the population. Nonetheless, applying
the findings obtained by grouping individual scores to determine the behavior of a single person involves a shift in level (a change from the interindividual variation to that of intra-individual variation in time and place). Based on the classical ergodic theorems, a classic branch of mathematics originally motivated by problems of statistical physics, Molenaar and Campbell (2009) argue that this shift in level is not valid for most cases in psychology, especially when we are dealing with developmental processes.

The classical ergodic theorems provide two rigorous conditions under which a shift in level from interindividual variation to that of intra-individual variation is possible and vice versa (Molenaar, 2004), thus allowing to define a phenomenon as ergodic. First, the same statistical model should apply to the data of all subjects in the population, suggesting a homogeneity in the study population. Second, the data must be stationary. More specifically, the data should have invariant statistical characteristics over time (i.e., it must have constant mean, variance, etc.). Accordingly, if either one (or both) of the conditions is not met, the psychological process we are dealing with is nonergodic (Molenaar & Campbell, 2009). Therefore the structure of its interindividual variation will differ from its structure at the intra-individual level of analysis. For all nonergodic psychological process, the results obtained in standard analysis of interindividual variation will not apply at the level of intra-individual variation and the other way around.

The question that concerns us here is whether flow can be considered an ergodic or a nonergodic process. In order to provide an answer to this question, we will review whether the process of work-related flow meets both ergodic conditions: homogeneity and stationarity.

**Condition 1: homogeneity**

The first condition for considering flow as an ergodic process is that each person in the population has to follow the same statistical model – that is, there has to be homogeneity in the population. In other words, the dynamics of the main variables describing the data should be invariant across subjects. For example, according to the flow theory, flow is greatly predicted by the balance between perceived challenges and skills (Fullagar et al., 2009; Moneta & Csikszentmihalyi, 1996). The homogeneity condition for ergodicity implies that the regression coefficients of challenge, skill, and the balance of the two must be invariant across people. However, when we look at empirical examples we find that the effects of challenge and skill and the balance between the two differ across individuals (Moneta & Csikszentmihalyi, 1996), so that, for instance, balance between challenges and skills is a strong predictor of flow for some individuals, while for other individuals this balance does not predict flow or even has a negative effect on the experience of the individual. Likewise, the effects of challenge, skill, and balance have been found to be linked to personality traits – such as achievement orientation, trait intrinsic motivation, and interdependent self-construal (Eisenberger, Jones, Stinglhamber, Shanock, & Randall, 2005; Moneta, 2004). Therefore, one of the main tenets of the flow model
Redefining flow at work

85

appears to be fully applicable only to some individuals. We have here a clear example of the violation of the homogeneity condition for being able to consider flow an ergodic process. More specifically, the intra-individual models appear to differ between subjects regarding how the balance between challenge and skill affects the flow experience of employees.

In an unpublished research (i.e., Paredes, 2012) that we have conducted measuring challenge and skill during twenty-one consecutive working days in a sample of sixty workers (6,981 registers obtained), we found that these two critical variables for the flow theory show different correlation values across individuals (Table 5.1). In this way, there are participants in which there is a positive correlation between challenge and skills; there are participants who present a negative correlation between these variables; and, finally, there is also a third group of participants in which these variables are unrelated. These results provide a clear evidence of the nonhomogeneity across subjects in flow at work.

Condition 2: stationarity

The second condition for ergodicity is that flow should have constant statistical characteristics over time (i.e., stationarity). In other words, the statistical parameters of the data, such as standard deviation and mean, should remain invariant across all time points. Molenaar and Campbell (2009) state that prime examples where this condition is violated are developmental processes, which almost by definition have statistical characteristics that change across data points. In this sense, Rathunde and Csikszentmihalyi (2006) define flow as a developmental process, due to the fact that every flow experience contributes to the growth of the self. After every episode of flow, employees are a little different from what they were before, as they have increased their skill level regarding a specific task.

When we look at empirical findings from research using longitudinal ESM data, we find that work-related flow is highly unstable and strongly dependent upon situational conditions (e.g., Fullagar & Kelloway, 2009; Guastello, Johnson, et al., 1999). In a study of work-related flow, Ceja and Navarro (2009) used the standard deviation value and the mean squared successive difference (MSSD; Von Neumann, Kent, Bellison, & Hart, 1941) to assess variations in response over time, such as fluctuations in the flow components. The authors chose to use the MSSD since they

<table>
<thead>
<tr>
<th>Correlation</th>
<th>Number of participants</th>
<th>% of participants</th>
<th>Average value of the correlation</th>
<th>SD value of the correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>12</td>
<td>20</td>
<td>0.504</td>
<td>0.236</td>
</tr>
<tr>
<td>Negative</td>
<td>33</td>
<td>55</td>
<td>-0.465</td>
<td>0.193</td>
</tr>
<tr>
<td>No correlation</td>
<td>15</td>
<td>25</td>
<td>-0.008</td>
<td>0.101</td>
</tr>
</tbody>
</table>

TABLE 5.1 Distribution of participants according to within-person correlations between challenge and skills (adapted from Paredes, 2012)
were interested in the variability over time of the flow variables; the range of the scale used was from 0 to 100. The results from this study are shown in Table 5.2.

In Table 5.2 we can observe the average number of records per participant (N = 20 participants), minimum and maximum per flow measure, and the mean value and standard deviation. In this case the standard deviation gives us information on the persistence of flow or its stability; as we can see all standard deviations and MSSD values are high, showing instable behavior for all variables.

Likewise, Ceja and Navarro (2009) found that when time series coming from both measures of flow (measure 1 and measure 2) were presented in line graphs (an example of measure 1 and 2 is shown in Figure 5.1), fluctuating dynamics are revealed.

Likewise, Fullagar and Kelloway (2009) found that 74% of the overall variance in work-related flow can be attributed to intra-individual variation. Similarly, a study by Rodríguez-Sánchez et al. (2011) found a curvilinear daily flow pattern, with lower levels of flow during working hours and higher levels of flow at the end of the day. All these studies demonstrate that the concept of flow denotes change and evolution over time. Hence, it becomes clear that flow is a nonstationary

<table>
<thead>
<tr>
<th>Variable</th>
<th>Number of records per participant</th>
<th>Minimum</th>
<th>Maximum</th>
<th>M</th>
<th>SD</th>
<th>MSSD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flow measure 1</td>
<td>119</td>
<td>0</td>
<td>49.30</td>
<td>9.28</td>
<td>7.98</td>
<td>50.40</td>
</tr>
<tr>
<td>Flow measure 2</td>
<td>119</td>
<td>0</td>
<td>100</td>
<td>64.96</td>
<td>22.61</td>
<td>55.24</td>
</tr>
</tbody>
</table>

FIGURE 5.1 Measures of flow 1 and 2 (adapted from Ceja & Navarro, 2009)
Redefining flow at work

This is a clear violation of the stationarity condition for ergodicity: constant statistical parameters of the data over time.

As we can see from the foregoing analysis, flow can be considered a clear example where the two conditions for ergodicity – homogeneity of population and invariant statistical characteristics over time – are not met, and therefore we are talking about a nonergodic process (i.e., its structure of interindividual variation differs from its structure of intra-individual variation). Because flow appears to be a person-specific process (i.e., the flow process obeys person-specific dynamic models), its analysis must be based on intra-individual variation (Hamaker, 2012).

For this kind of process the nonlinear dynamical systems (NDS) theory offers a wide variety of methods that focus on within-person dynamics (e.g., Guastello, Koopmans, & Pincus, 2009). Therefore, in our view, the NDS approach has a great deal to contribute to theory and empirical work on flow, as it examines person-specific models across time. More specifically, this approach gives us tools to assess the complexity of each person’s fluctuating behavior respecting the nonergodic characteristics of work-related flow. It can also help researchers in tackling individual differences in the pattern or shape of a participant’s variations. Whether assessing the quantity – or the quality and style – of a person’s changes, the focus is on finding indexes of intra-individual change that can be related to optimal levels of flow. The following section will tackle the second objective of this chapter: to explore the utility of NDS theory to enhance our understanding of work-related flow.

NDS theory: a promising approach to studying the dynamics of work-related flow

The NDS approach, also known as complexity theory, emerged during the 1960s from different theoretical and empirical approximations (e.g., general systems theory, chaos theory, fractal geometry, catastrophe theory, fuzzy sets theory; e.g., Guastello, 2002). These theories come from a wide variety of disciplines that share a common interest: the study of specific characteristics of complex systems, such as the existence of nonlinearity and deterministic chaos, fractal structures, catastrophic changes, and fuzzy boundaries (Munné, 2005). They propose a systemic view in which variables relate with one another continuously in a nonlinear way. This way, variables are antecedents and consequences simultaneously, generating emerging properties through their interaction. These types of systems are denominated as complex adaptive systems (Navarro, 2005).

Psychologists in general have shown increased interest in the application of NDS theory to the study of human processes and they obtained important empirical outcomes, predominantly in developmental (e.g., Smith & Thelen, 1993), social (e.g., Nowak & Vallacher, 1998), and organizational psychology (e.g., Guastello et al., 2009). The application of NDS models to positive organizational processes is not too plentiful; nonetheless, the link between nonlinear change and positive
psychology has been demonstrated theoretically (Schuldberg, 2006, 2007), as well as in empirical studies that have examined positive organizational behaviors like high work motivation (Arrieta, Navarro, & Vicente, 2008) and, more recently, work-related flow (Ceja & Navarro, 2009, 2011; Guastello, Johnson, et al., 1999; Navarro & Ceja, 2011). For a revision about the relations between nonlinear dynamics and positive organizational behavior see Navarro and Rueff-Lopes (2015).

Overall, there is evidence to suggest that complexity, change, and nonlinearity are integral to employee well-being. In other words, the relationship between work and employee flourishing is not strictly linear and stable over time; on the contrary, employee well-being seems to be rather unpredictable, with sudden, discontinuous, or unexpected changes (Schuldberg, 2006, 2007). Hence, NDS theory offers an interesting framework from which to study positive psychological processes like flow at work, providing an alternative perspective to the current prevailing paradigm, which emphasizes linear change (i.e., the overuse of techniques based on the general linear model assume the idea of proportionality and gradual change in the relations among variables). There are two key concepts of NDS theory that, in our view, can open interesting avenues for future research on work-related flow: chaotic behavior and catastrophic changes.

**Chaos and work-related flow**

Chaos refers to a particular nonlinear dynamic, and it can be viewed as a centerpiece of NDS theory (Guastello, 2002). The chaos phenomenon was discovered by Lorenz (1963) largely by chance while he was developing his work on weather forecasting, and it was later coined by Li and Yorke (1975). It can be defined as “aperiodic bounded dynamics in a deterministic system with sensitive dependence on initial conditions” (Kaplan & Glass, 1995, p. 27). According to Tsonis (1992), the concept of chaos underlies two fundamental epistemological truths in science. First, apparently random behavior (e.g., epidemic dynamics, behavior of stock market prices) is actually the result of simple deterministic rules. In other words, deterministic laws can produce behavior that appears random. Second, a chaotic phenomenon is best modeled using nonlinear techniques, such as recurrence analysis and catastrophe models, to name a few, which usually work with time series.

Chaotic behavior shows various fundamental characteristics (Guastello, 2002; Kaplan & Glass, 1995). First, chaotic behavior is unpredictable; this is to say that the dynamic never passes the same point twice. The unpredictability of chaotic behavior makes it resemble a random dynamic, especially when using techniques that are unable to capture the nonlinear structure of the dynamic (e.g., traditional linear statistical techniques). Second, chaotic behavior displays sensitivity to initial conditions, which means that even mild and brief inputs at a specific point in time can have important consequences in the long run. This property is also known as the butterfly effect. For example, in weather forecasting, seemingly trivial inputs—such as the flap of a butterfly’s wings in one region of the world—can disproportionally determine weather conditions in another place (Lorenz, 1993). The sensitivity to
the initial conditions is connected to the unpredictability of the dynamic in the long term. Third, chaotic dynamics exhibit clear boundaries, meaning that the dynamic stays within a confined range of values. Fourth, chaotic behavior is deterministic, meaning that it is regulated by simple deterministic equations.

The discovery of chaos has important implications for work and organizational psychology. For instance, the notion of prediction takes on new aspects when seen through the lens of chaos. As stated before, one of the main characteristics of chaos is that it is unpredictable in the long term. Hence, what organizational scholars thought was simple becomes complex, and questions arise regarding measurement, predictability, and verifications of classic theories regarding organizational behavior. In compensation, phenomena that appear random or stochastic may in fact be following simple rules. More specifically, a great part of the within-individual variability observed in organizational behavior that was previously conceived as random error can now be identified as obeying deterministic rules.

The last few decades have been fruitful for NDS theory in terms of the development and improvement of different methodologies for identifying and measuring deterministic chaos, such as the recurrence analysis, the surrogate data analysis, the Lyapunov exponents, the Kolmogrov entropy, the Hurst exponents, and catastrophe modeling, to name a few. These techniques allow researchers to identify the type of dynamic (i.e., chaotic, linear, or random) underlying in time series, and to know the amount of variables involved in the dynamic (see Heath, 2000; Ramos-Villagrana & García-Izquierdo, 2011).

Based on the fruitful advancements of NDS methodologies for identifying and measuring chaos in time series, examples of chaotic behavior have been detected among different disciplines (e.g., for the physical sciences, see Prigogine & Stengers, 1984; meteorology, see Lorenz, 1993; organizational behavior, see Guastello, 2002, or Navarro & Arrieta, 2010; physiology, see Freeman, 1991; psychology, see Barton, 1994, or Guastello et al., 2009). The manifestation of chaos in a wide variety of fields supports the universality of chaos proposed by Cvitanovic (1989), who suggested that chaotic behavior is universal and therefore can be observed in a wide variety of phenomena across all scientific disciplines, meaning that different systems are governed by the same rules — for example, the same rules can be operating in physiological systems and organizational behavior. One of these universal rules is the appearance of variability of behavior in healthy systems.

**Healthy variability in the workplace**

Following the principle of the universality of chaos and of particular relevance to research on work-related flow, there is an intriguing and controversial literature in physiology suggesting that specific characteristics of complex systems — mainly chaos — are related to well-being and optimal organ functioning (e.g., Freeman, 1991; Goldberger, 1991). More specifically, there is strong evidence demonstrating the existence of chaos in the cardiac (Goldberger, 1991) and neurological (Freeman,
systems of healthy patients, in contrast to unhealthy patients, who show periodic or linear dynamics in both cardiac and neurological systems.

Based on these findings, organizational psychologists have also found a link between chaos and well-being (for a revision see Navarro & Rueff-Lopes, 2015). For example, Arrieta et al. (2008) demonstrated empirical evidence of chaos in the intraperson variability of highly motivated employees. Three pioneering studies on work-related flow showed similar results; when employees’ time series were analyzed, most employees revealed nonlinear or chaotic behavior, whereas linear dynamics were the exception (Ceja & Navarro, 2009, 2011; Guastello, Johnson, et al., 1999). Ceja and Navarro (2011), for instance, demonstrated that higher levels of flow are associated with chaotic behavior, whereas linear behavior is associated with feeling anxious, and apathy is linked to random behavior. The authors conclude that there may be such a thing as “healthy nonlinear variability,” and a decrease in such nonlinearity may indicate a decrease in employee well-being.

In light of the foregoing findings, understanding the structure and behavior of chaos may provide further insights regarding employee well-being and can open new directions for future research on work-related flow. It appears that flow behaves mainly in a chaotic manner; therefore, NDS methodologies (e.g., recurrence plots, surrogate data, catastrophe modeling) that are able to describe and model chaotic behavior have a great deal to contribute to theory and empirical work on flow. Such methodologies can substitute, in some cases, or complement, in others, classical linear approaches by offering new tools with which scholars are able to study and model the linear and nonlinear evolution of work-related flow in an integrative manner. In this sense, it is important that future studies continue to examine the pattern of change observed in the intra-individual variability of flow.

An important question that would benefit from further conceptual development as well as empirical research is what variables are responsible for the emergence of different dynamical patterns (i.e., chaotic, random, or linear) observed in work-related flow. Ceja and Navarro (2011) found that high levels of the core components of flow (e.g., balance of perceived challenge and skill, merging of action and awareness) are associated with the emergence of chaotic behavior. Likewise, employees’ job features such as more seniority, longer job tenures, a full-time job contract, low flexibility of working hours, and a typical weekly schedule are linked to chaotic behavior. Future research could explore in more detail these findings. For instance, it seems that productive organizational behavior (e.g., to experience flow at work) requires specific boundaries in labor conditions in order to contain these creative outbursts. Studies exploring organizational facilitators of work-related flow, distinguished in previous flow research (e.g., Bakker, 2005; Demerouti, 2006), and their association with chaotic behavior may also help to shed further light on this issue. Likewise, recent studies recognize work engagement as a primary condition for experiencing work-related flow (Moneta, 2010). Hence, it may be interesting to further study the role of work engagement in the emergence of chaos in the intraperson variability of flow.

Overall, future research is needed to clarify the dynamic patterns underlying work-related flow across time; the variables responsible for the emergence of distinct dynamical patterns, especially the emergence of chaotic patterns; and the role...
of other related constructs (e.g., work engagement, mindfulness) in the relationship between chaos and flow.

**Catastrophe theory and flow: modeling abrupt and discontinuous change**

It has been demonstrated that work-related flow presents continuous fluctuations, generally nonlinear, across time (Ceja & Navarro, 2009, 2011; Guastello, Johnson, et al., 1999). Based on the catastrophe theory, Ceja and Navarro (2012) modeled for the first time the abrupt and discontinuous changes observed in the process of flow at the intra-individual level. Catastrophe theory (Thom, 1975; Zeeman, 1977) offers an alluring approximation for modeling the fluctuating reality of work-related flow. It is interested in describing and modeling the discontinuities that can appear in the evolution of a system. A catastrophe can be understood as abrupt or drastic changes that emerge as a consequence of small changes in the external conditions (Guastello, 1987). Catastrophe theory has been successfully used in different areas of work and organizational psychology, such as accidents involving health care workers (e.g., Guastello, Gershon, & Murphy, 1999), work motivation (e.g., Guastello, 1987, 2002), employee turnover (e.g., Sheridan, 1985), personnel selection (e.g., Guastello, 1982), workplace bullying (Escartín, Ceja, Navarro, & Zapf, 2013), and organizational change (e.g., Bigelow, 1982), among others.

More specifically, catastrophe theory provides an adequate conceptual framework as well as the mathematical tools for studying and modeling the possible nonlinear relationships between control parameters or independent variables and order parameters or dependent variables. There are seven elementary catastrophe models, whose degree of complexity depends upon the number of order (dependent variable) and control (independent variable) parameters. The cusp catastrophe model, one of the simplest and most widely used, explains the discontinuous change between two stable states of behavior by means of two control parameters and one order parameter. Work-related flow has been recently modeled as a cusp catastrophe (Ceja & Navarro, 2012; Navarro & Ceja, 2011; see Figure 5.2).
To illustrate the topographic differences between a cusp catastrophe model of flow and a traditional linear regression model, we show in Figure 5.2 both models. In the left panel of Figure 5.2 the cusp catastrophe model of flow is shown, which describes the change in the order parameter or dependent variable (i.e., flow: average of enjoyment, interest, and absorption) as a result of the interaction between perceived challenge and skill. In the right panel of Figure 5.2 a traditional linear regression model is shown containing the same set of variables. What differentiates both models is the fold shown in the catastrophe model, which indicates that for given values of the independent variables the dependent variable can present discontinuous or abrupt changes within the cusp region (represented by the fold region), whereas in the traditional linear regression this fold is not considered and sudden or abrupt changes are considered as outliers or noise in the data, and therefore this information is not included in the model.

Due to the topographic differences in the linear and nonlinear models, Ceja and Navarro (2012) hypothesized that a cusp catastrophe model could better capture the complexity and nonlinearity of the relationship between challenge-skill balance and work-related flow, compared to a linear regression model. Indeed, this was the case; findings from this study supported the better performance of the cusp catastrophe model over its linear counterpart (see Table 5.3) as shown by the lower AIC_c and BIC and higher $R^2$ indexes presented by the catastrophe model. The authors suggest that the superiority of the cusp catastrophe model for modeling flow is due to

### Table 5.3 Fit statistics for linear, logistic, and cusp models (adapted from Ceja & Navarro, 2012)

<table>
<thead>
<tr>
<th></th>
<th>Linear</th>
<th>Logistic</th>
<th>Cusp</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flow</td>
<td>AIC_c</td>
<td>978.95**</td>
<td>503.47</td>
</tr>
<tr>
<td></td>
<td>BIC</td>
<td>989.71**</td>
<td>516.79</td>
</tr>
<tr>
<td></td>
<td>$R^2$</td>
<td>.23</td>
<td>.44</td>
</tr>
<tr>
<td>Enjoyment</td>
<td>AIC_c</td>
<td>1031.31**</td>
<td>363.70</td>
</tr>
<tr>
<td></td>
<td>BIC</td>
<td>1031.79**</td>
<td>376.94</td>
</tr>
<tr>
<td></td>
<td>$R^2$</td>
<td>.19</td>
<td>.47</td>
</tr>
<tr>
<td>Interest</td>
<td>AIC_c</td>
<td>1018.69**</td>
<td>981.09</td>
</tr>
<tr>
<td></td>
<td>BIC</td>
<td>1026.02**</td>
<td>1001.33</td>
</tr>
<tr>
<td></td>
<td>$R^2$</td>
<td>.24</td>
<td>.38</td>
</tr>
<tr>
<td>Absorption</td>
<td>AIC_c</td>
<td>994.54**</td>
<td>785.73</td>
</tr>
<tr>
<td></td>
<td>BIC</td>
<td>1005.09**</td>
<td>799.05</td>
</tr>
<tr>
<td></td>
<td>$R^2$</td>
<td>.20</td>
<td>.35</td>
</tr>
</tbody>
</table>

Note: The AIC, BIC, and $R^2$ were calculated as the average of all participants. The trimmed mean was used in order to eliminate outliers or extreme observations, discarding 5% of the values at the high and low ends. AIC_c = Akaike information criterion corrected; BIC = Bayesian information criterion. $N = 6,981$ logs across 60 participants. The chi-square likelihood ratio test was calculated for the AIC_c and BIC indexes. ** p < .0001.
its capacity to model both linear and nonlinear relationships as well as gradual and discontinuous changes in an integrative way. Likewise, Navarro and Ceja (2011) examined the application of a cusp catastrophe model to modeling flow in work and nonwork activities; the results demonstrated the better performance of the cusp catastrophe model over its linear counterpart (i.e., linear regression model) in both domains. Moreover, Ceja and Navarro (2012) found that perceived challenge plays an especially important role in the dynamics of flow, as it indicates the number of discontinuities in employees’ work-related flow.

In view of the foregoing findings, flow at work seems to present discontinuous as well as continuous changes across time. Therefore, catastrophe theory appears to be an adequate approximation for modeling this combination of changes. Moreover, it enriches our capacity to understand, characterize, and integrate different patterns of change (e.g., gradual and continuous as well as abrupt or discontinuous). In our view, future research on work-related flow should continue examining the application of the different models proposed by catastrophe theory (e.g., elementary cuspoids; see Guastello, 1987) to study changes in flow among different employee populations.

There are three interesting avenues for future research in this area. First, further research is needed to compare the performance of catastrophe models to that of more traditional statistical linear approaches (i.e., linear regression analysis, HLM, growth curve modeling). Second, perceived challenge seems to be the variable responsible for the emergence of bifurcations. In other words, perceived challenge appears to present a threshold beyond which two divergent behaviors are possible (i.e., low and high levels of flow). Hence, future research is needed to examine the role of challenge and other variables (e.g., dimensions of flow, organizational facilitators of flow) as determinants of the phase transitions as employees move into and out of an optimal experience. Likewise, it would be interesting to study whether the specific values of perceived challenge at which the bifurcation point is created are distinct for each employee or whether similarities in terms of threshold can be found between different employees. Third, an interesting area for future research may be to study situation- and person-related predictors of the sudden and abrupt changes observed in work-related flow over time. On the whole, research in this area will surely add valuable information to the flow theory.

In the following section we will describe several approaches for assessing intra-individual variability in work-related flow relying on NDS theory. Afterwards, we will propose some important implications for practitioners as well.

**Implications for academics and practitioners**

At the beginning of this chapter we argued that flow can be considered as a nonergodic developmental process. This suggests that our analyses should be framed in a within-person approach that examines how the process of flow unfolds within individuals across time. Likewise we have presented the utility of the NDS approach for studying the dynamic behavior of flow over time, emphasizing chaotic dynamics
and catastrophic changes as two fruitful concepts that may contribute to the development of a new mind-set for understanding work-related flow as a highly dynamic process. This section will be focused on the implications that the incorporation of this new mind-set, framed in the NDS approach, can have for the work developed by flow scholars and practitioners.

**Implications for flow research: NDS methodologies for analyzing within-person data**

Since the 1970s, the methodologies of NDS and their applications to social research have exploded (Guastello & Gregson, 2011). Specialist journals (e.g., nonlinear dynamics, psychology, and life sciences) and books (e.g., Guastello & Gregson, 2011; Heath, 2000; Kaplan & Glass, 1995) provide us with methods and applications of the behavioral sciences that are useful for studying the intricate and constantly changing nature of flow. In this sense, as flow scholars, we have in our hands an array of useful methodologies that can help us examine flow data with new lenses. In this section we will suggest a step-by-step basic procedure for assessing and modeling intraperson dynamics in time-series data. It is important to emphasize that the methodologies described here require a minimum set of data. For example, we have worked with at least 100 observations taken over time for each of the individuals being studied. However, with a minor amount of registers (thirty or forty) some of the techniques that we have used can be applied. In any case, the longer the time series, the better the accuracy of the results.

Likewise, it is important to note that using NDS methodologies does not mean that we should throw away all that we know about flow. Instead, it indicates a remarkable opportunity to go beyond what we already know about work-related flow and build on new models from variables we know well, incorporating nonlinear dynamics. Up until now the traditional linear approaches, grounded on the generalized linear model (GLM), have considered nonlinear dynamics as random noise. Likewise, although our approach in the present chapter is quantitative, qualitative designs using an NDS approach are also feasible, and several organizational behavior scholars are actively involved in performing qualitative studies from an NDS approach (e.g., Langley, Smallan, Tsoukas, & Van den Ven, 2013).

In Figure 5.3, a procedure of time series analyses using NDS methodologies that has been used in several studies (e.g., Ceja & Navarro, 2009, 2011, 2012; Arrieta et al., 2008; Ramos-Villagrasa & García-Izquierdo, 2011) is described. The process starts by producing line graphs of flow indexes against time for each participant separately (see first column in Figure 5.4). This will give us a within-subject perspective that will enable us to observe the presence or absence of regular patterns in the dynamics of flow over time. Visual inspection of flow indices against time is helpful to describe the dynamics of time series and it is needed before attempting more complicated analyses (Chatfield, 1996). For those participants for whom this preliminary visual inspection shows that their time series are mainly linear or nearly linear, a traditional approach based on the GLM is recommended (e.g., ARIMA
models). However, for those cases where the line graphs show instable or nonlinear dynamics and it is challenging to discriminate between linear and nonlinear behavior, the use of NDS methodologies is advised.

Once we have visually assessed the nature of our time series and we detect unstable dynamics, we can go further and conduct a deeper analysis of patterning of
FIGURE 5.4 Line graphs (left) and recurrence plots (right). The top row shows a linear dynamic, the middle row a chaotic dynamic, and the lower row shows a random dynamic pattern. Adapted from Ceja & Navarro (2011)
Redefining flow at work

trajectories, the paths defined by each participant’s data set, allowing us to uncover the dynamic patterns (e.g., linear, chaotic, or random) underlying the time-series data. In this chapter we will describe three NDS techniques that assess dynamic patterns in time-series data: maximum Lyapunov exponent, recurrence analysis, and surrogate data testing. In our view the three techniques presented here should be used together so the researcher can achieve a more precise examination of the intra-individual variability of flow (as chaotic, linear, or random), by integrating results from the three techniques.

The maximum Lyapunov exponent is a quantitative indicator of the dynamic patterns underlying time series. The Lyapunov exponent is based on a concept of entropy, which is the rate at which information that allows forecast of a variable $y$ is lost (Kaplan & Glass, 1995). In the case of a linear pattern, the maximum Lyapunov exponent is zero or less; otherwise, it could be chaotic or random. However, it is important to note that the Lyapunov exponent can overestimate chaos because for some cases it is not sensitive enough to discriminate between chaos and random behavior. In the cases of random patterns, Lyapunov exponents become very large, and this may be an indicator of random patterning in the data. Likewise, finding a pure linear pattern in a time series is very unlikely, increasing the risk of accepting a case as nonlinear when it is actually following a linear pattern. In order to continue our analysis further we suggest using also recurrence plots. Lyapunov exponents can be calculated in R using fNonlinear or RTisean packages.

The recurrence analysis is based on the study of possible recurrences in a time series. A recurrence is a sequence of events that repeats itself across time (Marwan, Romano, Thiel, & Kurths, 2007). The NDS offers a powerful tool for the characterization of recurrence called recurrence plots. A recurrence plot is a square matrix, in which the matrix elements correspond to those times at which time-series data recur (columns and rows indicate a certain pair of times). More specifically, the recurrence plot reveals all the times when the phase space trajectory of the data visits roughly the same area in the phase space (Heath, 2000). The recurrence plot enables us to characterize the dynamic underlying the time-series as linear, chaotic, or random. A free and useful software for applied recurrence plots is included in the fNonlinear package in R.

In Figure 5.4 we show line graphs (left) and recurrence plots (right) of flow data obtained from the study by Ceja and Navarro (2011). The first row of figures represents a linear dynamic; in this type of dynamic the recurrence plot shows an image in which all the data points are clearly concentrated in a few specific areas. This can be interpreted as the system passing several times through the same positions, which indicates that the dynamic is very regular and stable.

The middle row represents a chaotic dynamic; in this case the recurrence plot exhibits a uniform tone of upward marked diagonals called “recurrences” parallel to the main diagonal. These recurrences are sequences of values that are repeated within the system in a similar way at different periods of time that characterizes a chaotic time series. The last row represents a random dynamic; in this case any result is possible and many points appear across the graph. There is a lack of structure,
showing the absence of any recurrence. Although the visual recurrence approach is very useful, it presents an important challenge: the visual interpretation of recurrence plots requires some experience and for some cases it may be difficult to distinguish between random and chaotic dynamic patterns; hence the decision-making can be very subjective.

Both Lyapunov exponent and recurrence analysis enable scholars to perform a preliminary discrimination between linear, chaotic, or random patterns underlying time series. Nevertheless, it is important to use a third quantitative technique to clarify further the dynamic pattern underlying the time series. This third technique is called surrogate data analysis (Schreiber & Schmitz, 2000). Surrogate data analysis is used to verify the randomness of time series. The logic behind the surrogate data is very simple: starting from the original time series, this procedure enables the creation of random series, which conserve the same statistical properties (e.g., mean, variance, and structure of auto-correlation) as the original series, but remove nonlinear dependency (Kugiumtzis, 2002). Afterwards, a hypothesis contrast is conducted between the original series and the surrogate data, with the objective of ruling out that the original time series is also random (see Heath, 2000). The procedure is implemented in the TISEAN software (surrogates command) now also available in R (RTisean package). Readers interested in learning more about the basic concepts behind the surrogate data analysis are advised to review the work by Dolan and Spano (2001) and Heath (2000).

After carefully assessing the nature of the intra-individual variability using line graphs, Lyapunov exponent, recurrence analysis, and surrogate data analysis, for those cases in which the dynamic pattern is characterized as nonlinear or chaotic, a further step can be to develop dynamic models to match the empirical data. This is an area where there is a good deal of room for fruitful research on work-related flow. In this sense, catastrophe theory approach has been extensively applied in the social sciences (Bigelow, 1982; Guastello, 1995; Guastello, Gershon et al., 1999) and more recently in work-related flow (Ceja & Navarro, 2012) for modeling the discontinuities in nonlinear or chaotic data. To analyze the fit of the cusp catastrophe model to the flow data there are several powerful techniques available to flow scholars, such as the multivariate GEMCAT (see Lange, McDade, & Oliva, 2001; Oliva, Desarbo, Day, & Jedidi, 1987) or the polynomial regression technique (see Guastello, 1982, 1987). Nonetheless, we recommend using the R cusp package (Grasman, van der Maas, & Wagenmakers, 2009). This method implements and extends Cobb’s maximum likelihood approach (Cobb & Watson, 1980; Cobb, Koppstein, & Chen, 1983) and makes it easy to fit the cusp catastrophe model to real flow data and compare it with linear and logistic regression models. It is important to note that considering the nonergodic nature of flow data, the fit of each model (i.e., cusp catastrophe, linear, and logistic) should be done individually for each study participant (i.e., case per case).

Summing up, results of preliminary visual explorations using line graphs can serve us to verify the stability of flow over time. Subsequently, if our data shows unstable behavior across time, NDS techniques, such as Lyapunov exponent, recurrence
analysis, and surrogate data analysis, can help us to determine the type of dynamic pattern (i.e., linear, chaotic, or random) underlying the flow data and select the most suitable methodology for modeling our data. More specifically if the data shows linear behavior we can use more traditional linear approaches, such as ARIMA models or other related ones. However, if the flow data behaves in a nonlinear manner, flow scholars can use NDS modeling techniques, such as catastrophe models. Finally if the data shows random behavior, no modeling of the flow data can be conducted.

Overall, flow can be considered a nonergodic process; thus, it is better studied using person-specific dynamic models. In this sense, techniques based on NDS can help flow scholars to incorporate in their research the nonlinearity and discontinuous change that employees experience in their everyday struggle of transitioning between nonflow states (e.g., boredom or anxiety) and the flow state. It is important to emphasize that between-subjects designs can also be used; however, they should be based on the intra-individual analysis of single cases. For instance, flow scholars can study clusters of participants presenting different dynamic patterns (e.g., linear, chaotic, or random). In a study on work-related flow, Ceja and Navarro (2011) found that high levels of flow are associated with the chaotic pattern, whereas other states of consciousness are associated with linear and random patterns. Future research on flow can continue this line of research and examine the variables associated with the emergence of different dynamic patterns in flow at work. We are hopeful that new developments in the study of flow at work will have more widespread applications of NDS-based methods.

Implications for practitioners: incorporating nonlinear dynamics of flow to organizational practice

A growing number of organizations are aligning work and culture with the principles of flow, considering the main tenets of the flow theory to create working conditions that allow their employees to experience flow (e.g., balance between challenges and skills, clear goals, unambiguous feedback, autonomy, space for deep concentration). Some examples are Microsoft, Gallup, Ericsson, Media-Saturn Group, Patagonia, and Toyota, which have discovered that creating a flow-friendly work environment that helps individuals flourish can increase productivity and satisfaction at work (Pink, 2009).

Csikszentmihalyi (1996) argues that without flow there is no creativity, and in today’s business world, innovation and creativity are a requirement to succeed. “To stay competitive, we have to lead in the world in-person creativity. People with high flow never miss a day. They never get sick. Their lives are just better and they are more productive,” says Jif Clifton, CEO of the Gallup Organization. Cheng and Van de Ven (1996) found that the creative processes in organizations exhibit chaotic patterns. In other words, learning in chaotic conditions is an expanding and diverging process of discovering possible action alternatives, while learning under stable periodic conditions is a narrowing and converging process. Hence, it appears that flow and creative processes emerge under chaotic conditions, meaning that
instability and variability in organizational contexts can be regarded as flow-friendly work conditions.

Utho Creusen, former chief human resources officer of Media-Saturn Group, received an excellence in practice award by the Gallup International Positive Institute in 2006 for institutionalizing concepts of flow in his company. Utho explains that opportunity and freedom within a work role are needed to experience flow. This is difficult when roles conform to a standardized template. Hence, it is important to allow some flexibility within roles no matter how structured the working environments. It is always important that individuals have certain degree of flexibility to be able to craft their jobs.  

Likewise, at Patagonia, former CEO Michael Crooke argues that the experience of flow can be extended from the Patagonia workforce to all stakeholders if they derive a joyful experience from the company (Perschel, 2010). Crooke implemented an annual company assessment to measure the degree of work-related flow employees experience in their daily activities, including items such as how free employees are to use their own time (sense of control), whether they experience a balance between their job demands and their skills (challenge-skill balance), and whether they are able to stay focused in one task at a time (deep concentration). Crooke has been celebrated for building Patagonia into one of the world’s most recognized, successful, and socially responsible brands (Persche, 2010).

Stefan Falk, former vice president at Ericsson, adopted flow concepts to engage employees at his company (Pink, 2009). Impressed by the results, Falk developed a flow-based culture in 2003 when he joined Green Cargo, one of Scandinavia’s largest transport and logistics companies. At Green Cargo, Csikszentmihalyi’s book on flow is required reading for all managers as part of a training program. With the objective of establishing clear goals and unambiguous feedback (two of the antecedents of flow), employees and managers meet and negotiate three-month contracts and organize feedback sessions once a month. A year following this implementation, Green Cargo substantially increased its profits (Pink, 2009).

Another example of how companies use the flow theory to enhance the experience of their clients is Microsoft applying the concepts of flow to give Windows users a more engaging and joyful experience. Its objective is to make its products a pleasure to use. Likewise, Microsoft is currently conducting research on how flow might improve the lives and productivity of software engineers (Pink, 2009).

As we have seen in the foregoing examples, enhancing work-related flow can be neither costly nor difficult for organizations. For instance, monitoring the flow experiences of employees to develop person-specific interventions to enhance flow at work may be really powerful. NDS methodologies can give practitioners a more dynamic view of flow, where variability and abrupt changes are seen as a positive and healthy behavior. In this sense, practitioners should be careful with employees who show stable dynamics of flow (e.g., they never enter the flow zone or they never leave the flow zone), as stable dynamics appear to be associated with low levels of flow at work (e.g., Ceja & Navarro, 2011).
Likewise, as we have shown throughout the chapter, practitioners can benefit from the NDS approach for understanding work-related flow as a dynamic and unique process that is different for each individual. This should be viewed as a fundamental management tool, and can guide organizations in the creation of individual-specific interventions that consider the dynamic pattern of each individual (chaotic, random, or linear) and the characteristics of the work context. With this information in mind, designing individual job positions or entire work environments following the concept and dynamics of flow will likely result in higher well-being for all stakeholders in organizations.

Conclusions

Our conclusions can be framed in three main “take-home” messages. First, flow should be considered a nonergodic process, meaning that we need to study it at the intra-individual level of analysis. Once we can describe the dynamic of flow at the intra-individual level, we might be able to group individuals in clusters following the same dynamic patterns.

Second, flow should be considered a nonlinear process. This means that we need to study it going beyond the techniques that the generalized linear model provides us with. More specifically, we should apply nonlinear techniques to obtain better results in our research.

Finally, flow should be present in the agenda of managers and human resource professionals. The experience of flow represents one of the purest manifestations of intrinsic motivation, and motivation is a key determinant of performance at work. Additionally, intrinsic motivation enhances employee well-being. One of the classic paradoxes for human resource professionals is taking care of employee motivation and well-being while enhancing organizational productivity – this can be managed by paying attention to the dynamics of flow at work. Definitely, taking care of employees’ flow is a serious business.

Notes

1 In Ceja and Navarro (2009) two flow measures were used: measure 1 was the balance of challenges and skills, and measure 2 involved the average of enjoyment, interest, and absorption.


3 Personal interview with Utho Creusen at the Gallup Positive Psychology summit, 2008.

References


Redefining flow at work


Redefining flow at work

(Eds.), Oxford handbook of methods in positive psychology (pp. 423–436). New York: Oxford University Press.


