Title: Dynamic patterns of flow in the workplace: characterizing within-individual variability using a complexity science approach

Keywords: flow, well-being, dynamic patterns, within-individual variability, chaos

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Organizational researchers are increasingly embracing a within-person perspective to study employee well-being. This is evidenced by a number of studies adopting longitudinal designs and experience sampling methodologies to capture fluctuations in well-being at work across time (e.g., Beal & Ghandour, 2010; Heller, Watson, & Ilies, 2006; Judge & Ilies, 2004; Reis, Sheldon, Gable, Roscoe, & Ryan, 2000). Following this encouraging trend, the present study introduces a *nonlinear dynamical systems* approach, also known as a *complexity science approach*, to characterize the intraindividual variability of flow experiences in the workplace. With nonlinear dynamical systems theory at its basis, the aims of the current study are threefold. The first goal is to examine whether flow exhibits both linear and nonlinear patterns. The second objective is to study if nonlinear patterns (i.e., chaotic dynamics) are associated with higher well-being (i.e., high levels of flow). The third goal is to sift out some of the variables associated with different dynamical patterns of flow (i.e., chaotic, random or linear) while engaging in work-related activities.

Flow and Well-Being at Work

Flow is a concept at the core of research on employee well-being (Diener, 2000; Seligman & Csikszentmihalyi, 2000). Developed in relation to the aim to understand intrinsically motivated behavior, *flow* refers to “a state in which people are so involved in an activity that nothing else seems to matter; the experience itself is so enjoyable that people will do it even at a great cost, for the sheer sake of doing it” (Csikszentmihalyi, 1990, p. 4). Research on flow contributes to the creation of knowledge regarding two aspects that are of central importance to employee well-being (Diener, 2000; Nakamura & Csikszentmihalyi, 2002; Seligman & Csikszentmihalyi, 2000). First, it provides valuable insights regarding the nature, origins and consequences of optimal experience in the workplace. Second, it unravels the conditions that act as obstacles or facilitators to this optimal experience.

Researchers have identified that flow occurs when people perceive a balance between the challenge of a situation and their own skills to deal with this challenge (Asakawa, 2004; Csikszentmihalyi, 1990; Moneta & Csikszentmihalyi, 1996). When this balance is achieved, people experience one or several characteristics of flow, including loss of time awareness, merging of action and awareness, high levels of concentration, perceptions of control over actions and environment, unambiguous feedback, loss of self-consciousness, clarity of goals and an autotelic experience (Csikszentmihalyi, 1990; Jackson & Csikszentmihalyi, 1999; Nakamura & Csikszentmihalyi, 2002). In contrast, when individuals perceive incongruities between challenges and skills, experiences of boredom, anxiety, or apathy may result (Csikszentmihalyi, 1990; Massimini & Carli, 1988).

Flow experiences are suggested to be intrinsically rewarding because they allow employees to become intensely involved in an activity and stretch their abilities to the limit (Csikszentmihalyi, 1990, 1997). Consequently, a job that repeatedly gives the opportunity to perform challenging yet manageable tasks is likely to have benefits for employees (e.g., positive mood, see Eisenberger, Jones, Stinglhamber, Shanock, & Randall, 2005; high levels of satisfaction, see LeFevre, 1988; high levels of self-efficacy, see Salanova, Bakker, & Llorens, 2006; and high self-esteem, see Wells, 1988) and the organizations they work for (e.g., commitment, see Csikszentmihalyi, Rathunde, & Whalen, 1993; task interest and organizational spontaneity, see Eisenberger et al., 2005).

The flow theory emphasizes the phenomenology of employees' interaction with their work environment (Shmidt, Shernoff, & Csikszentmihalyi, 2007). It acknowledges the dynamic system that is developed by employees in relation to their work environment, recognizing that a worker experience is a product of the interaction with his or her environment at a specific moment in time (Nakamura & Csikszentmihalyi, 2002). While this interactional viewpoint is fundamental to flow theory, capturing empirically the interplay between employee and environment can be very challenging. These difficulties are reflected in the fact that most research on flow in the workplace has mainly focused on cross-sectional slices or static snapshots of flow (e.g., Bakker, 2005; Demerouti, 2006; Eisenberger et al., 2005) and survey-based longitudinal studies with time lags of months (e.g., Salanova et al., 2006) trying to analyze differences between persons. Although these between-person approaches have made valuable contributions for advancing the flow theory, they present an important limitation: they are unable to capture within-individual fluctuations over time.

With the aim of moving flow research beyond between-person approaches, empirical investigations are beginning to focus on dynamic assessments of intraindividual variation over time (e.g., Debus & Sonnentag, 2009; Fullagar & Kelloway, 2009). Considering that most of the variance in flow at work seems to be within-person (Fullagar & Kelloway, 2009), pursuing dynamic approaches that contemplate these fluctuations as meaningful information is crucial for advancing our understanding of flow at work.

From Static to Dynamic Perspectives of Flow and Well-Being in the Workplace

Our understanding of employee well-being increasingly relies on dynamic examinations of within-individual variability as it unfolds naturally across time (Ilies, Dimotakis, & De Pater, 2010; Ilies, Schwind, & Heller, 2007; Reis et al., 2009). This new dynamic perspective complements more traditional between-person approaches, which usually use cross-sectional designs and emphasize individual differences in average levels of well-being (Diener, 1996, 2000), by analyzing how these levels vary as a function of person and context factors.

Within-persons research is important for several reasons. First, it takes into consideration temporality and therefore has the potential to capture intraindividual variability in well-being over time. In contrast, between-person approaches have difficulties when it comes to capturing these fluctuations and they often treat this variance as random error. Yet this variability is likely to be meaningful and associated with important work outcomes (Dalal & Hulin, 2008; Diener, Suh, Lucas, & Smith, 1999). Second, it gives a better and more fine-grained understanding of how psychological processes change over time and how they relate to person and situation factors and their interaction. By contrast, between-person approaches are limited in their capacity to model the causes and consequences of such variability over time (Reis et al., 2000). Third, processes that govern momentary experiences may not be the same as those operative at the between-person level of analysis (Reis et al., 2000). Hence, studying within-individual variability may provide new insights into linkages between life experiences and well-being.

The value of within-individual perspectives is being actively explored and has provided valuable insights on the effect of various factors such as daily social support (Ilies, Johnson, Judge, & Keeney, 2010), skill variety and autonomy (Fullagar & Kelloway, 2009), spillover effects across work and non-work domains (Illies et al., 2007; Sonnentag, 2003) and the impact of positive and negative events on employee well-being (Beal & Grandour, 2010 ; Dimotakis, Scott, & Koopman, 2010; Sonnentag & Zijlstra, 2006).

Considering the inherent theoretical and practical difficulties associated with studying intra-individual well-being trajectories over multiple occasions, it is remarkable how many valuable outputs the within-person perspective has managed to accomplish. These insights are generally framed in terms of describing cause-effect relations (Guastello & Liebovitch, 2009; Vallacher & Nowak, 1997). The methodologies used to model this type of relations are often based on traditional models and techniques of linear data analysis (e.g., correlations, analysis of variance, SEM, HLM, etc). These methods are ideal for addressing all types of linear change.

However, these methods will likely miss the fine nonlinear or chaotic structure (e.g., where a change in one variable can have a disproportionate impact on the state of other variables) generated by behavioral processes over time (Gregersen & Sailer, 1993; Vallacher & Nowak, 1997). Poor analytical results (e.g., low R^2 values and lack of statistical significance) are to be expected when analyzing nonlinear behavior with standard linear statistical methods (Guastello, Koopmans, & Pincus, 2009). Moreover, the variance that linear models are not able to explain is commonly considered as forms of “error” (e.g., measurement error, omission of important variables, etc); when it may be a consequence of treating a nonlinear process as linear.

As a result, it is fundamental that we carefully assess the nature of the within-individual variability we are researching and ascertain whether it potentially fits a linear or nonlinear profile (Gregersen & Sailer, 1993; Vallacher & Nowak, 1994). The nonlinear dynamical systems (NDS) theory offers new constructs and methodologies that complement more traditional linear approaches. It does so by distinguishing three main types of temporal patterns that may exist in a longitudinal data time series: linear, chaotic or random (Heath, 2000; Morrison, 1991). To achieve this, the NDS theory conceives the current state of the system – that is, the variable’s current value – as a function of its preceding state (Van Geert, 2009). This emphasis on the dynamic properties of a system contrasts with the conventional linear approach, in which a variable is described as a function of other variables without paying much attention to feedback mechanisms. In this regard, while the linear approach is interested in studying samples or populations in which to test relationships between variables, the dynamic approach is more interested in studying the changes and evolution of a process over time via the analysis of systematic registers of the process (time series).

The capacity to characterize the intraindividual variability of flow as chaotic or nonlinear (i.e., unstable dynamic patterns but with the presence of regularities), linear (i.e., regular and stable dynamic patterns across time) or random (i.e., a total absence of any pattern) is important for several reasons. First, it allows researchers to choose the appropriate data analysis techniques depending on whether they are dealing with a linear or nonlinear process. And second, this information provides researchers with important insights regarding their capacity for predicting the future behavior of the process under research. More specifically, if flow behaves linearly, the future behavior of the process can be modeled and predicted. In contrast, if flow behaves chaoticly, the variables that we use to describe the process have critical (or threshold) values, and beyond these values, even slight changes in one variable can produce major changes in other variables, hence we cannot make long-term predictions.

A Nonlinear Dynamical Systems Theory Approach to the Study of Intraindividual Variability in Flow

The nonlinear dynamical systems (NDS) theory refers to the “study of how complex processes unfold over time and is sometimes known as chaos theory or complexity theory” (Guastello et al., 2009, p. 13). More specifically, the NDS theory seeks to describe and explain change and therefore extends our knowledge regarding the dynamical patterns and variability that up to date, based on traditional linear approaches grounded on the GLM (Generalized Linear Model), have been considered random noise. However, with the aid of methods grounded in the NDS theory, we are likely to find that for some cases this randomness is in reality hiding an underlying deterministic structure which is chaotic or nonlinear in character.

The chaotic or nonlinear behavior shows various fundamental characteristics (Kaplan & Glass, 1995). First, nonlinear behavior is unpredictable, which refers to the fact that the dynamic never visits the same point or value twice. Unpredictability represents the lack of periodicity in nonlinear and chaotic dynamics that can resemble a random dynamic with no apparent structure if it is not analyzed using the appropriate methodologies. Second, nonlinear behavior shows sensitivity to initial conditions, which means that trivial inputs at a specific point in time can have major effects in the long run. Such an amplifying effect occurs as a consequence of the nonlinear feedback loops that emerge within the system. The sensitive dependence on the initial conditions is responsible for the unpredictability of the dynamic. Third, the dynamic is deterministic, meaning that it is regulated by simple rules. Fourthly, nonlinear behavior shows bounded dynamics to such an extent that the system stays in a finite range of values. As Mathews, White, and Long (1999, p. 445) state, chaotic behaviors “never explode into unconstrained growth.”

Advances in NDS theory provide mathematical tools for identifying and measuring deterministic chaos, such as graphic procedures (e.g., recurrence plots or delay graphs) and quantitative methods (e.g., surrogate data, Lyapunov exponents or the correlation dimension). As a result, examples of chaotic behavior are being found among different disciplines, such as the physical sciences (e.g., Prigogine & Stengers, 1984), physiology (e.g., Freeman, 1991; Goldberger, 1991), meteorology (e.g., Lorenz, 1993), ecology (e.g., Olsen, Truty, & Schaffer, 1988), economics (e.g., Arthur, 1989), sociology (e.g., Dendrinos & Soins, 1990) and psychology (e.g., Barton, 1994; Guastello, 2002; Navarro & Arrieta, 2010). In short, researchers have discovered chaos in the behavior of a great number of nonlinear processes; demonstrating the universality of chaos (Cvitanovic, 1989). This universality means that insights regarding the chaotic behavior of, for example, physiological systems can be applied to understand the chaotic behavior of organizational processes.

In organizational psychology, scholars have also shown increased interest in identifying chaotic dynamics in employee well-being. For example, Losada and Heaphy (2004) found that flourishing business teams are associated with chaotic behavior. Arrieta, Navarro, and Vicente (2008) showed that the intraindividual variability of employees presenting high levels of work motivation is characterized as chaotic. Likewise, two pioneering studies (Ceja & Navarro, 2009; Guastello, Johnson, & Rieke, 1999) based on longitudinal designs, have used the NDS theory as a framework to characterize the within-individual variability of flow. The findings from both studies show similar results. When employees’ time series are analyzed, most individuals show nonlinear or chaotic dynamics, while participants revealing linear and random dynamics are the exception.

If organizational research is revealing an association between chaos and flow, the next step should be to ask why researchers are finding chaos in the study of flow. Let us consider Csikszentmihalyi's (1993) processes of differentiation and integration. According to the flow theory, to experience flow, the person must recognize a challenge or opportunity for action; this involves a process of differentiation. To recognize a challenge, the person needs to become flexible and open to new possibilities, seek out novelty, be curious, experimental and adaptable (Csikszentmihalyi, 1993, 2003). The process of integration relates to the acquisition of skills; as the person gains mastery of a challenge, the skills involved in the activity become part of his or her stock of skills (Csikszentmihalyi, 1993). The process of integration equips the person with wider information processing strategies and greater variability in perspectives as well as resilience in the face of new challenges. According to the flow theory, only when the processes of differentiation and integration combine harmoniously can a person experience flow (Csikszentmihalyi, 1990, 1993).

The interaction between the processes of differentiation and integration opens the possibility to the emergence of nonlinear or chaotic dynamics. In short, both processes produce a permanent tension as they act in opposite directions: the process of differentiation destabilizes employees as they must face new challenges. On the other hand, the process of integration has primarily a stabilizing effect, as employees need to incorporate new skills to their stock of personal abilities. The necessary continuous balance between both processes can be characterized as unpredictable (e.g., unexpected changes can occur in the work context, giving rise to new and unforeseen challenges that employees must face) and sensitive to initial conditions (e.g., small changes in the challenges faced by employees can result in disproportional effects in the integration process, such as was the case when new IT tools were introduced into the workplace and millions of employees had to upgrade their skills to keep doing their jobs).

The communalities between flow and chaotic systems raise the possibility that the complex dynamics of chaos underlie flow behavior across time. Moreover, there is empirical evidence that flow behaves mainly in a chaotic way (Ceja & Navarro, 2009; Guastello et al., 1999). Considering all of the above reasoning, we make the following prediction: *chaotic* *dynamics will predominate over other types of dynamics (i.e., linear or random) in the within-individual variability of flow*.

Chaos: A Healthy Dynamic in the Workplace

Following the universal characteristics of chaotic systems (Cvitanovic, 1989) we can consider research in physiological well-being that examines the intraindividual variability of healthy organ functioning across time. Such studies present strong empirical evidence of chaos in the cardiac (Goldberger, 1991) and neurological (Freeman, 1991) systems of healthy patients, as opposed to unhealthy people, who show periodic and stable dynamics in both cardiac and neurological systems. In this sense, there is some consensus in the field of physiology that healthy organ functioning is associated with chaotic dynamics. Physiology scholars have invoked “healthy variability” and a decrease in this variability can indicate a decrease in health (Kaplan et al., 1991). According to Schuldberg (2006), one appeal of such a thesis is that systems presenting chaotic dynamics tend to respond flexibly (Skarda & Freeman, 1987) and show creative behavior (Richards, 1990), important attributes of well-being (Fredrickson, Tugade, Waugh, & Larkin, 2003). Moreover, this malleability allows chaotic systems to adapt to a continuously changing environment (Goldberger, 1991).

Similar properties can be found in flow experiences. The broaden-and-build theory of positive emotions (Fredrickson, 1998, 2001) provides us with a useful framework from which to study the links between high levels of flow and chaos, as it associates positive states with one of the properties of chaotic processes: unpredictability. Fredrickson’s theory holds that positive states (e.g., flow) broaden the array of thoughts and actions called forth (e.g., play, exploration), facilitating generativity and behavioral flexibility, whereas negative emotions narrow those same arrays of thoughts and actions. This generativity and behavioral flexibility makes people less predictable in positive states than in negative states (Fredrickson & Losada, 2005). The link between positive emotions and unpredictability has been demonstrated empirically at different levels of analyses. Fredrickson and Branigan (2005) found that people induced to experience positive emotions reported a wider array of impulses to act in the moment, which made their behavior harder to predict. Likewise, Schuldberg and Gottlieb (2002) found that people's positivity predicted higher variability and complexity within their moment-to-moment moods. Looking at married couples, Gottman, Murray, Swanson, Tyson, and Swanson (2003) discovered that happier couples were associated with more variability and flexibility from moment to moment interactions; nevertheless, over time, these couples were the ones more likely to continue their relationship for long periods of time. Furthermore, Fredrickson and Losada (2005) found that human flourishing is associated with non-repetitive, innovative and flexible interactions with the environment, representing the complex properties of chaos. Therefore, employees who experience high levels of flow at work are likely to be less predictable, as they seek novelty and opportunities for action and they are adaptable and flexible.

According to the "healthy chaos" consensus in the field of physiology and in line with the broaden-and-build theory of positive emotions (Fredrickson, 1998, 2001), we expect that *high levels of flow will be associated with the chaotic dynamic while low or medium levels of flow will be associated with linear or random dynamics*.

Variables Associated with the Emergence of Different Dynamical Patterns in Flow

If we confirm the existence of different dynamical structures underlying the intraindividual flow variability, the next step would be to address the variables responsible for the emergence of these dynamical patterns (i.e., chaotic, linear and random). To identify these variables, we focus on the key elements that, according to the literature, are at the core of the flow experience, as well as various individual and job characteristics that should affect the experience of flow at work.

In terms of the core elements of flow, the flow theory has identified several key component states (Csikszentmihalyi, 1990, 1993; Jackson, 1996; Jackson & Csikszentmihalyi, 1999). The first key component of the experience is a *balance of perceived challenges and skills*. The second is a *merging of action and awareness*, meaning that one's involvement in an activity is so intense that the behavior becomes spontaneous and automatic. The person is not aware of anything else but the task at hand. Third, the activity provides *unambiguous and clear feedback* regarding how one is performing the task at hand. The fourth component is an extremely *high level of concentration* on the activity at hand; all the psychic energy is directed towards the task at hand and there are no distractions. Fifth, the person feels *in control* of the activity. Sixth, a *loss of self-consciousness* occurs as all concern for self disappears and the person becomes one with the activity. The seventh component is a *loss of time awareness*. Eighth is *a clarity of goals*. And ninth, *the autotelic experience*. Moreover, the variables of enjoyment, interest, and absorption are also suggested to be at the core of the flow experience (Hektner, Schmidt, & Csikszentmihalyi, 2007). In this sense, if chaos represents a healthy dynamic in the workplace, we will expect that *high levels of the above component states will be associated with chaotic behavior*.

Several studies also show that flow is experienced more often in the work context than in other non-work domains (Csikszentmihalyi & LeFevre, 1989; Delle Fave & Massimini, 1988). The authors argue that the lack of flow in leisure time is due to an inability to organize one's psychic energy in unstructured free time. Indeed, “most leisure time is filled with activities that do not make people feel happy or strong” (Csikszentmihalyi & Le Fevre, 1989, p. 821). In this sense, work characteristics that bring structure and direction to the psychic energy of employees, such as type of job contract (full-time/part-time), flexibility of working hours and week schedule, will most likely have an effect on flow. More specifically, a full-time job contract, structured working hours (low flexibility of working hours) and a typical week schedule (i.e., five working days and two days of rest) might provide employees with higher opportunities to fill their days with activities that have the necessary structure for experiencing flow.

Moreover, age and tenure (i.e., job tenure) have been shown to affect the manner in which work environment features combine to influence employee well-being (e.g., Bedeian, Ferris, & Kacmar, 1992; Bedeian, Pizzolato, Long, & Griffeth, 1991; Kacmar & Ferris, 1989). More specifically, older employees and employees with longer job tenures tend to be associated with higher levels of job satisfaction (Bedeian et al., 1992). Hence, senior employees and people with longer job tenures might have more opportunities for experiencing flow.

Although more research is needed to draw conclusions regarding the relation between type of job contract (i.e., full-time and part-time), degree of flexibility of working hours, week schedule, age, job tenure and flow, these variables are likely to elicit valuable information regarding the factors that are associated with the emergence of the various dynamical patterns (i.e., chaotic, linear or random) encountered in the within-individual variability of flow.

Hence, the core components of the flow experience and various individual and job characteristics make up our framework for characterizing the different dynamical patterns disclosed by participants. Based on this framework we expect that *high values of the key components of flow* (e.g., balance of perceived challenges and skills, merging of action and awareness, etc.) *will be more associated with the chaotic pattern than with the linear and random patterns*. In addition, we also expect that *employees who are more senior, have longer job tenures, a full-time job contract, low flexibility of working hours and a typical week schedule, will be more associated with the chaotic pattern than with the linear and random patterns*. It is important to underscore that these predictions are largely exploratory, due to the paucity of published research on the variables associated with the emergence of different dynamical patterns in flow.

Summary of Research Objectives

With the aim of examining novel and interesting approaches to the study of repeated assessments of well-being, this present study considers the experience of flow in the workplace from a nonlinear dynamical systems approach. More specifically, based on the NDS theory, the aims of the current study are threefold: (a) to examine whether flow exhibits linear, nonlinear or chaotic patterns, (b) to study if chaotic dynamics are associated with higher well-being, as reflected by higher levels of flow and, (c) to examine the variables associated with the emergence of different dynamical patterns (i.e., chaotic, linear and random) in flow.

Method

Participants

A total of 60 employees from various occupational backgrounds participated in the study. The sample was heterogeneous in terms of sex, age, occupation and origin, which allowed us to study flow experiences at work within a wide range of subject profiles. There were 28 males and 32 females; the mean age was 38, ranging from 26 to 64; 8% had high school diplomas, 57% had undergraduate degrees and 35% had postgraduate degrees. The participants had worked an average of 8 years at their companies (minimum 1 month and maximum 43 years); they had been in their current positions an average of 6 years (minimum 1 month and maximum 28 years); they dedicated an average of 8.3 hours per day (minimum 4 hours and maximum 14 hours) and 42 hours per week (minimum 16 hours and maximum 84 hours) to work. Some of the jobs occupied by the participants were as follows: Chief Executive Officer, researcher, office worker, manager, assembly line worker, human resources advisor, law firm partner, architect, clinical nutritionist, dog trainer, clinical psychologist, chef, high school teacher, university professor, marketing director, professional dancer, real estate salesman, scuba diving instructor, sports trainer and travel agent.

Participants were reached through personal contacts, either directly by the researchers or via third parties. Requirements for inclusion in the study were to have a full-time or part-time employment and a high level of commitment to the study. Participants did not receive any financial compensation for taking part in the research study. When they finished the study, participants received personal feedback sessions regarding their levels of flow in the workplace.

Design and Procedure

Given its solid reputation for studying flow, the experience sampling method (ESM) was utilized (e.g., Delle Fave & Bassi, 2000; Hektner et al., 2007; Moneta & Csikszentmihalyi, 1996). ESM allows researchers to monitor variations throughout the day and is particularly effective at capturing the temporal and dynamic nature of the work experience (Hektner et al., 2007), a feature that we find vital for the present study. Data were collected by handheld personal digital assistants (PDA). Participants were given a PDA that produced six signals per day, at random times during working hours. They were required to answer six questions at each signal (for further details see Instruments section). This process was repeated over a period of 21 days, until at least 100 trials were completed.

In addition, during the study, participants were interviewed on three occasions. The first interview was conducted on day one of the study, during which general demographic information was gathered (e.g., age, sex, educational level, type of work). At this interview, participants were told how to use the PDA and how to answer the flow diary. The researcher also discussed with them the operative definitions of all the variables included in the diary, and a few examples were provided to make sure they understood the meaning of all the terms included in the study. The second interview was carried out halfway through the study; and participants were asked to give feedback to the researcher regarding their experience in the study so far. The final interview, which took place at the end of the study, included a total of twenty-nine open questions (see Instruments section for details).

Instruments

Two instruments (a flow diary and semi-structured interview) were developed as complementary strategies to gain a richer account of participants' flow experiences at work. The flow diary featured six questions covering several variables, which, as suggested by the flow theory (Csikszentmihalyi, 1975, 1990; Stein, Kimiecik, Danields, & Jackson, 1995), are at the core of the experience of flow: activity, perceived challenge, perceived skill, enjoyment, interest, and absorption. Specifically, the questions in the flow diary were as follows:

1. What activity am I performing at this moment?
2. How challenging do I find this activity?
3. What is my skill level for performing this activity?
4. How much do I enjoy doing this activity?
5. How interesting is this activity?
6. How quick does time pass while I'm doing this activity?

The first question aimed at focusing the individual's attention on a specific activity (the one being performed when the PDA beeped), so that the other questions were answered with this activity in mind. This question was open and the person had to write a brief description of the activity being performed (e.g., 'I am drafting the financial budget for a project'). The remaining questions were linked to a measurement scale (a continuous line blocked off at either end) with the following labels: 'A little' and 'A lot' for question numbers 2, 3 and 4; 'Very interesting' and 'Slightly interesting' for question number 5; and 'Time passes very fast' and 'Time passes very slowly' for question number 6. For question 2-6 the participants were asked to place a mark on the line that appeared directly on the screen (scale) and the PDA automatically converted the mark into a 0 to 100 scale.

The semi-structured interview was composed of twenty-nine questions aimed at collecting information regarding individual and job characteristics (age, job tenure, week schedule, contract type and flexibility of working hours) and the key elements considered nuclear to the experience of flow (Csikszentmihalyi, 1990, 1993). Hence, some of the questions addressed by the interview are the following: *balance of perceived challenge and skills* (whether employees generally find a balance between perceived challenge and skill in their daily work-related activities); level of *skills (*whether employees perceived they had the sufficient level of skills for performing their job-related activities well *);* level of *challenge* (whether employees perceived their work-related activities as challenging); the perception of *merging of action and awareness* (how often employees perceive to be so involved in a work-related task that they lose awareness of everything but the task at hand); *unambiguous and clear feedback* (whether employees receive clear feedback regarding their work activities); *high levels of concentration* (whether their work context allows them to achieve high levels of concentration); *control of the work activities* (whether employees feel they are in control of their job-related tasks); *clarity of goals* (whether employees have clear goals in their work); *loss of self-consciousness* (how often employees feel so involved in a work-related activity that all concern for self disappears); *transformation of time* (how often employees lose track of time when involved in work-related activities); and *the autotelic experience* (how often employees experience an enjoyable and intrinsically rewarding job-related activity).

All the questions were open-ended and the responses were coded into different options. For example, the question regarding “unambiguous and clear feedback” was investigated through the following question: “Do you generally receive clear feedback on how well you have performed your work-related activities?” Participants provided open answers, which were then revised and coded by two researchers into three categories (yes/sometimes/no). To ensure the reliability of the coding process, an inter-coder reliability measure suggested by Miles and Huberman (1994) was used to calculate the level of agreement between the two coders. The measure yielded over 90 % of inter-coder reliability. To further confirm the reliability, disagreements between coders were settled through an exchange of views.

Analysis

The analyses used in the present study were twofold, divided in terms of their primary objectives. The first group of analyses focused on studying the dynamic behavior of flow at work over time. To this end, two indexes of flow were created, based on the information obtained from the flow diary (flow measure 1 and 2). Both measures were analyzed using methodologies that rely on the complexity theory approach. The second group of analyses was devoted to studying the relations among the flow values (from indexes 1 and 2 and flow measure 3), the different dimensions of the flow experience and different individual and job characteristics, with the emergence of distinct dynamic patterns.

Measuring flow.

Two indexes of flow were calculated following the most commonly measured conditions of flow (Csikszentmihalyi, 1988, 1990, 1997). The first index (flow measure 1) was developed following the suggestions of Guastello et al. (1999), in which the flow variable consists in the cross-product of the participant’s perceived skill and challenge levels recorded for each activity divided by the cross-product of the within-person standard deviations for skill and challenge. The second index (flow measure 2) was created using Hektner’s (1996) procedure of computing the geometric mean (i.e., square root of the product) of raw-scored challenge and skill. These two flow indexes were significantly correlated (see Table 1). .

Additionally, a third measure of flow (flow measure 3) was calculated based on the four states of consciousness defined in terms of balance of challenges and skills developed by the flow theory (Csikszentmihalyi, 1975; Csikszentmihalyi & LeFevre, 1989; Massimini, Csikszentmihalyi, & Carli, 1987), which differentiates between flow, anxiety, boredom and apathy. More specifically, we first calculated the mean value of skill and challenge for each participant; subsequently, to determine which of the four challenge and skill contexts participants were in, we applied the following rules: if both challenges and skills were greater than the respondent's average, they were assigned to the flow state category; if challenges were greater than the respondent's average, and skills were less than his or her average, they were assigned to the anxiety state category; if challenges were less than the respondent's average, and skills were greater than his or her average, the boredom state was assigned; and if both challenges and skills were below the respondent's average, the apathy state was assigned. In order to estimate the correlation between this measure and the indexes mentioned before (flow index 1 and flow index 2), we quantified de percentage of time that each participant spent in the flow context. These results can be viewed in Table 1.

Analyzing the dynamics of flow.

With the aim of identifying the type of dynamics (random, chaotic, or linear) underlying the intraindividual variability of flow, the time series related to the created indexes were analyzed using the following methods: line graphs, recurrence analysis and surrogate data analysis. Line graphs of the flow indexes (flow measures 1 and 2) for each participant were produced. The information displayed by these graphs enabled us to observe the presence or absence of regular patterns in the dynamics. In addition, they indicated whether the flow dynamics showed continuity or discontinuity.

All time series were then studied using statistical methods grounded in the NDS theory. Specifically, we first used the recurrence analysis (using VRA 4.7 software), followed by the analysis of surrogate data (using TISEAN 3.0.1 software).

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 over time (Marwan, Romano, Thiel, & Kurths, 2007). The NDS theory provides a powerful tool for the characterization of recurrences called *recurrence plots*. The *recurrence plots* allow us to identify the type of dynamic (i.e., linear, chaotic or random) underlying the time series. More specifically, when the dynamic is linear, the recurrence plot shows a graph in which all of the data points are concentrated in a few specific areas. This can be interpreted as the system passing several times through the same positions, which means that the dynamic is very regular. When the dynamic is random, the graph shows a uniform tone indicating a lack of structure, in other words, it shows the absence of any recurrences. Finally, if the dynamic is non-linear or chaotic, the graph exhibits a uniform tone, similar to the random dynamic, but it shows the presence of small lines parallel to the main diagonal. These lines are recurrences, sequences of values that are repeated within the system in a similar way at different periods of time (for a more detailed explanation, see Heath, 2000). As we have explained before, this visual approach is very useful, but it presents an important limitation: for some cases, it can be difficult to characterize the dynamic as chaotic or random, hence the decision making can be very subjective.

In order to overcome this limitation, there is another powerful quantitative technique called *surrogate data* analysis (Schreiber & Schmitz, 2000). The logic behind the surrogate data is very simple: starting from the original time series this procedure enables a numerous set of new series to be generated, in which the data appear in a randomly disordered way. Afterwards, a hypothesis contrast is conducted between the original time series and the surrogate data, with the objective of ruling out that the original time series is also random (see Heath, 2000).

Analyzing the variables associated with the emergence of distinct dynamic patterns.

The second group of analyses focused on studying the association of different variables relevant to the flow experience and the emergence of distinct dynamic patters (i.e., chaotic, random, and linear). Taking into account the variety of information collected from our data (both quantitative and qualitative), the objective of the second group of analyses (correlational), the sample size, and the possibility of encountering a disproportion of cases when studying the different dynamical patterns (i.e., we will find many cases characterized by one pattern and a few cases characterized by another pattern) we used the multiple correspondence analysis (MCA). The MCA is an appropriate tool for capturing the covariance relationships between different variables regardless of their typology, sample size and the disproportion of frequencies concerning the values of the variables under consideration. The covariance relationships can be obtained through the well-known Benzécri-distance, which weighs the former frequencies in an inversely proportional fashion (see Benzécri, 1992; Cornejo, 1988). The most relevant strength of MCA is its multivariate nature, which allows for the multivariate treatment of several data synchronically (Chen & Gursoy, 2000). The MCA gives results in the form of coordinate graphs and, within these graphic representations, the physical proximity is interpreted as a covariance relationship. If we use continuous quantitative variables in the MCA, these are usually categorized in various levels, with the aim of facilitating the reading of the coordinate graphs.

Because the MCA allows the identification of relationships between variables but does not give the level of significance, a chi-square test was conducted for those variables that, as shown by the MCA, were clearly related to a specific dynamic pattern.

Results

The Dynamics of Flow in the Workplace

We have considered the descriptive results of the time series of all study variables, such as the mean number of registers considering all participants (116.3), maximum (177) and minimum number of registers (100), mean values, standard deviations and correlations of study variables (see Table 1). In this case, the standard deviations gave us key information regarding the inconsistency of variables, or their degree of instability. As we can see, standard deviation values are high, showing unstable behaviors for all study variables. Moreover, looking at Table 1, we find that the three flow indexes correlate strongly. It is important to note that at the between-persons level of analysis, level of challenge correlates highly with all three flow indexes, whereas skill is not significantly correlated to the indexes. However, at the within-persons level of analysis, challenge and skill are significantly correlated with flow index 1 and 2, supporting the argument that factors that govern intraindividual processes may not be the same as those operative at the between-person level of analysis.

Moreover, we may be witnessing some collinearity between challenge and the indexes we have used in the present study. More specifically, they appear to be reflecting more the level of challenge than the conceptual combination of challenge and skill (see the Strengths and Limitations section for further discussion on this topic). Nevertheless, the three indexes correlate significantly with other correlates of flow including enjoyment, interest and absorption, giving support to the flow theory and to the indexes we have used.

INSERT TABLE 1 HERE

As we can see from Figure 1 (left-hand side) simple line graphs reveal the fluctuating dynamics of flow over time (especially in the second and third cases). Nonetheless, from these line graphs it is not possible to detect any pattern, and this is why recurrence analysis is useful to reveal any hidden pattern in the data. Figure 1 (right-hand side) also shows three recurrence plots corresponding to the same cases as the line graphs (corresponding to flow measure 1), and it can be observed how this technique is helpful for revealing the different dynamics underlying the time series. The first case reveals a highly structured dynamic, in which data points are concentrated into very few areas of space, a hallmark of linear dynamics. The second case shows a relatively unstructured dynamic, but after careful inspection it reveals a number of lines parallel to the main diagonal that indicate the presence of a chaotic dynamic. Finally, the third case yields a highly unstructured dynamic showing no specific pattern, characteristic of a random dynamic.

INSERT FIGURE 1 HERE

A summary of the results obtained from the recurrence plots is shown in Table 2. The different patterns encountered in the within-individual variability of flow were chaotic (nonlinear and deterministic dynamics), random and linear (regular dynamics). The term “nonlinear or random” was used to identify those cases for which the distinction between chaotic and random dynamics was difficult to determine. After conducting the recurrence analysis, we proceeded with the surrogate data analysis with the aim of contrasting the results obtained from the recurrence analyses. These results are also shown in Table 2.

Taken together, the two types of analyses (recurrence plots and surrogate data) show that the predominant dynamical pattern in the within-individual variability of flow is the chaotic dynamic in 75% of cases, followed by the random dynamic encountered in 20% of cases, while as few as 5% of cases showed a linear dynamic. These findings suggest that flow in the workplace presents a high intraindividual variability and that it behaves predominantly in a chaotic manner, supporting our expectations.

INSERT TABLE 2 HERE

Chaos and High Levels of Flow

The MCA came up with five factorial axes that explained 99% of the total variance. Following the suggestions by Hair, Anderson, Tatham, and Black (1998), who recommended that an acceptable axis should represent a value equal to or larger than 0.20, a two-axis solution was adopted. The first axis (singular value = 0.53) explained 57% of the variance and the second axis (singular value = 0.20) accounted for 22% of the variance. Hence these two axes, which explained 79% of the variance, were used (see Table 3). The x-axis discriminated between the low levels of flow and medium/high levels of flow, whereas the y-axis distinguished between medium and low/high levels of flow (Figures 2, 3 and 4).

INSERT TABLE 3 HERE

With the aim of avoiding information overload regarding the solution obtained from the two axes of the MCA, we developed three graphs representing the relevant information for testing each of our expectations. Moreover, in order to facilitate the reading of the graphs, we created a series of information sections.

In Figure 2, we observe a clear association between the different levels of all variables presented with each of the dynamic patterns. We must remember that within these graphic representations the physical proximity is interpreted as a covariance relationship. Specifically, the low levels of flow for the two flow indexes are associated with the random pattern; while the medium levels of flow are linked to the linear pattern; and the high levels of flow correspond to the chaotic pattern. In other words, employees who showed a chaotic dynamic in their flow experiences are also the ones who experienced the highest levels of flow in their jobs. Additionally, low levels of enjoyment, interest, and absorption are situated close to the random pattern, whereas the medium levels are located halfway from the linear and random patterns. Likewise, the high levels are located close to the chaotic pattern. Therefore, participants who showed the highest levels of enjoyment, interest and absorption are also the ones who presented a chaotic dynamic in their flow experiences.

Following the four states of the challenge/skill ratio (Csikszentmihalyi & LeFevre, 1989), the apathy state was associated with the random pattern, the anxiety state was located near the linear pattern and the boredom state was situated in between the random and linear patterns; while the flow state was clearly linked to the chaotic pattern. In other words, participants who showed a chaotic pattern were likely to spend more time in the flow state.

In order to test the possible significance of these associations, chi-square tests were computed. These tests indicated that the association between flow measure 1 and the different dynamic patterns (chaotic, random and linear) was significant ($X^2 = 7.856$ (4 *df*), $p < 0{,}01$). It is necessary to remark that the chi-square might not be a good test for studying the results under the conditions of this study (with a clear disproportion between the three pattern categories: 75%, 20% and 5%). Instead, the MCA is recommended.

Summing up, the high level of the two indexes of flow and the flow state that highlight the balance between perceived skill and challenge ended up being associated with high levels of enjoyment, interest and absorption. Table 1 demonstrates that this association is significant. This result lends further support to the flow theory, which suggests that the combination of high skill and challenge should increase employee's task interest, absorption and enjoyment (Hektner, et al. 2007). Overall, these results clearly support our expectations.

INSERT FIGURE 2 HERE

Variables Associated with the Emergence of Different Dynamical Patterns in Flow

Figure 3 describes the associations between the core components of flow and the different dynamic patterns. We emphasize here the more significant associations. For example, the linear pattern is associated with the following values: the employee rarely perceives a balance between challenge and skills (i.e., balance of perceived challenge and skills: low); the employee perceives a medium level of skills (i.e., perceived skills: medium); the job is somewhat challenging (i.e., perceived challenge: medium); the employee perceives some clear goals (i.e., clarity of goals: medium) and the employee from time to time experiences an enjoyable and intrinsically rewarding job-related activity (autotelic experience: sometimes).

The chaotic pattern appears to be associated with several values: the employee perceives his or her job as challenging (i.e., perceived challenge: high); the employee is most of the time so involved in a work-related activity that he or she loses the awareness of everything else but the task at hand (i.e., merging of action and awareness: very often/always); the work context allows the employee to achieve high levels of concentration (i.e., levels of concentration: high); and the employee very frequently experiences an enjoyable and intrinsically rewarding job-related activity (i.e., autotelic experience: very often).

Finally, the random pattern is linked to the following values: for some work-related activities there is a balance between perceived challenge and skill (i.e., balance of perceived challenge and skills: medium); the employee perceives low levels of personal skills (i.e., skills: low); the employee is never very involved in a work-related task (i.e., merging of action and awareness: never); the employee never experiences an enjoyable and intrinsically rewarding job-related activity (i.e., autotelic experience: never); and the employee never loses track of time while being at work (i.e., transformation of time: almost never).

A chi-square test indicated that the association between the variable merging of action and awareness and the different dynamic patterns was significant (X^2 = 14.098 (4 *df*), p < 0,05). Summing up, the results from the MCA (Figure 3) show that high values of the key components of flow (e.g., balance of perceived challenges and skills, merging of action and awareness, etc.) are associated with the chaotic pattern, lending support to our expectations.

INSERT FIGURE 3 HERE

In Figure 4 we see how individual and job characteristics are associated with the different dynamic patterns. Again we emphasize here the more significant associations. As we can see from the graph, the linear pattern is associated with those employees who are in the 41-50 year-old age range, who have been working for less than 1.5 years at their current job and distributed their weekly work as follows: either three days at work and four days off work or six days of the week dedicated to work-related activities and 1 day to leisure activities. The chaotic pattern seems to be associated with employees who are over 50 years old, have been at their current job position for more than 15 years, have a normal week schedule (5 days work/2 days leisure), occupy full-time positions and have low flexibility of working hours. The random pattern is associated with those employees who are in the age range of up to 30 years old, have been in their job position from 5-15 years and spend 4 days at work and have 3 days for leisure.

In short, the results from the MCA (Figure 4) show that employees who are more senior, have longer job tenures, a full-time job contract, low flexibility of working hours and a typical week schedule, are more associated with the chaotic pattern than with the linear and random patterns. These results provide support of our expectations.

INSERT FIGURE 4 HERE

Discussion

The current study contemplates flow in the workplace, an important manifestation of employee well-being. With the NDS theory as the backdrop, our focus was on characterizing the evolution of the within-person variability of flow at work across time. Compared to the traditional linear approach, the NDS approach represents a shift in terms of philosophy (an acknowledgement that flow in the workplace changes and evolves over time, giving rise to different dynamic patterns), research methods (gathering systematic registers of flow over long periods of time using methodologies like the ESM) and statistical methods (the use of methods like recurrence analysis and surrogate data analysis that account for different dynamic patterns of flow: linear, random and chaotic).

The present study resulted in three main findings. First, we argued the importance of studying the evolution of intraindividual variability of employee well-being over time. The results of our study suggest that flow experiences in the workplace show a high degree of within-individual variability; and therefore a within-person approach is needed to explain that variability. This finding supports the acknowledgement of the flow theory that employees' experience is a product of the interaction with their environment at a specific moment in time (Nakamura & Csikszentmihalyi, 2002). In this sense, our study indicates that the within-persons approach complements between-persons perspectives, which usually miss intraindividual variability, by showing that the fluctuations of flow across time are meaningful and associated with the quality of working life. More specifically, the present study shows that different instances of such variability are linked to distinct states of consciousness (i.e., flow, boredom, apathy and anxiety) as well as different values of the core components of flow and various individual and job characteristics. Likewise, as indicated by the correlation analyses, the processes that govern momentary flow experiences appear to be different to those operative at the between-person level of analysis (e.g., perceived skill behaves differently in both levels of analysis). Hence, both between and within-persons approximations are necessary for a full understanding of employee well-being.

Moreover, the NDS techniques revealed that the intraindividual variability of flow contains important pieces of information for characterizing different dynamic patterns in this phenomenon. Specifically, this variability was characterized as chaotic for most of the cases (75%); while some cases (20%) showed a random dynamic; and a few cases (5%) showed a linear dynamic. These findings are consistent with previous studies (Ceja & Navarro, 2009; Guastello et al., 1999), which suggest that, in the majority of cases, flow behaves in a chaotic way; it is important to emphasize that the sample used in the present study is significantly larger compared to the former two studies (i.e., 20 and 24 participants respectively). These results could not be revealed using traditional linear techniques for data analysis, since they are limited to detect linear change. Although linear techniques are ideal for addressing all types of linear variability, they miss the fine nonlinear or chaotic structure that may exist in the fluctuating behavior of employee well-being, as shown in the present study.

A common assumption in linear data analysis techniques is that change is gradual and linear across time. However, this assumption is not valid where chaos is found. Chaos tells us that the process consists of a nonlinear dynamical system, which is neither stable and predictable nor stochastic and random. As Morrison (1991) argues, researchers should (1) use stochastic models and statistics to explain random processes; (2) use linear deterministic models to explain stable and periodic dynamics; and (3) use NDS approaches to explain chaotic processes. Consequently, it is paramount that researchers carefully assess the nature of the intraindividual variability they are examining and determine whether it reveals a linear or nonlinear pattern.

The capacity to characterize the within-person fluctuations of employee well-being as nonlinear, linear or random is relevant for various reasons. First, it allows researchers to accurately select the most suitable methodology depending on the dynamical pattern underlying the time series. Second, by knowing the structure underpinning the within-person variability, researchers are equipped with knowledge regarding their capacity for predicting the future behavior of the process under scrutiny. For example, if flow follows a linear pattern, changes in the intraindividual variability are expected to be regular; hence the future behavior of flow can be accurately predicted. In contrast, if flow behaves in a random manner, changes in the fluctuations are stochastic and therefore future predictions are unattainable. Likewise, if flow depicts a chaotic pattern, the variables involved in the process present nonlinear associations (e.g., variables are continuously involved in ongoing feedback processes); hence, researchers can only make short-term forecasts.

In view of the above, NDS techniques can complement linear approximations, which provide information exclusively about linear processes, by enriching our capacity to understand, conceptualize and characterize different patterns in the intra-individual variability of employee well-being. Hence according to our findings, research on employee well-being should benefit from embracing NDS concepts in its theorization and methodologies in order to go beyond what we already know.

As a second main finding, results of the current study show that high levels of flow are associated with the chaotic dynamic. Moreover, following the four challenge and skills states (Csikszentmihalyi & LeFevre, 1989), the flow state is associated with chaotic dynamics, whereas the anxiety state is associated with the linear pattern and the apathy state is linked to the random pattern. Likewise, high levels in the core components of flow (e.g., balance of perceived challenges and skills, merging of action and awareness, etc.) appear to be associated with the chaotic pattern, whereas medium and low levels in these components are linked to the linear and random patterns. Hence, there may be such a thing as “healthy variability” and if such variability becomes random or periodic, it may indicate a decrease in employee well-being.

The links between subjective well-being and chaos is being increasingly demonstrated empirically at multiple levels of analysis. At the individual level, employees experiencing high levels of work motivation depict chaos in their momentary experience (Arrieta et al., 2008). Looking at a broader manifestation of well-being, within married couples, happy marriages show flexibility and creativity equivalent to chaotic dynamics (Gottman et al., 2003). Likewise, within work groups, flourishing business teams are associated with deterministic chaos (Losada & Heaphy, 2004). Therefore, understanding the structure of chaos may provide a map of healthy functioning in organizations. In this sense, chaotic fluctuations in the variables that compose the optimal experience should be regarded as optimal functioning, whereas the loss of complex variability (i.e., linear or random dynamics) may occur in certain negative states of consciousness in the workplace, including anxiety or apathy.

Finally, as a third main finding, if chaos is related to higher well-being, we must stay alert regarding those components associated with the emergence of chaos in employee's fluctuating behavior. The present study shows that senior employees (above 50 years old) are associated with the chaotic pattern, whereas younger employees are linked to the random and linear patterns. It is important to mention that most senior employees in our sample occupied high positions within their organizations (e.g., CEO, high school dean, general manager of a health center, and head of marketing unit). Hence, a possible explanation for this finding may be that senior employees, due to their job positions, have more experience when dealing with challenging situations in their jobs and therefore are more capable of finding a balance between perceived challenge and skill. This association needs further research and therefore emphasizes new possibilities for future research on flow and chaos. Similarly, we found that those job characteristics (e.g., longer job tenure, full-time contract, no flexibility of working hours and typical week schedule) that bring structure and direction to the psychic energy of employees seem to be associated with the emergence of the chaotic pattern. On the other hand, job characteristics that provide less structure to the psychic energy of workers (e.g., part-time contract, high flexibility of working hours, etc.) are linked to the linear and random dynamics. This means that having structure in certain job characteristics is likely to promote the emergence of the chaotic pattern. By identifying the variables responsible for the emergence of different dynamic patterns in flow (i.e., chaotic, linear and random), organizations may be able to promote the emergence of chaotic dynamics or “healthy within-individual variability.”

Practical Implications

The high degree of deterministic chaos found in the present study has three important practical implications for fostering employee well-being. First, we can learn from our findings that the chaotic variability found in flow should not be understood as anomalous functioning that should be avoided. Rather, it should be regarded as a dynamic, positive, and healthy behavior. In this sense, pursuing stability regarding employee well-being may not be a realistic goal for organizations. Second, we know that chaos is deterministic. More specifically, if flow behaves in a chaotic way, we know that the process is governed by specific rules (i.e., it is not random). In this sense, managers can have a big influence on employees’ optimal experiences by intervening on specific variables, instead of trying to affect a large number of factors. For instance, a small intervention that clarifies the objectives of a work-related activity can have major effects on employee well-being. Third, chaos is characterized by being unpredictable. In other words, managers must realize that they can only predict the outcome of an intervention for promoting optimal experiences in the short term and cannot make predictions in the medium and long term. In this sense it should seem normal that an intervention for promoting flow in work-related activities can produce different effects when applied at different times to the same group of employees.

By understanding the unpredictability of flow over time, one would expect to find discontinuities and changes in employees’ optimal experience, and it would be no surprise to discover that an activity that resulted in flow for a worker during a specific year fails to do so the following year. This uncertainty should not be regarded as an obstacle for promoting employee well-being in organizations but instead should be viewed as a fundamental management tool (Navarro, 2006). Indeed, according to our study findings, unpredictability is an important characteristic of high levels of flow. Hence, managers should refrain from using "standard" interventions and pay more attention to the context and initial conditions in which their interventions are taking place. In this sense, case studies can be a good tool for learning about how to foster flow in the workplace.

Strengths and Limitations

Three main strengths of the present study should be stressed. First, the study utilized the ESM technique with a sample of 60 employees (research studies using this methodology commonly use students as their study population). Second, employees were monitored over a long period of time (21 days), obtaining a total of 6,981 registers. This is a key aspect if our aim is to characterize the dynamic of flow across time. Third, the study used methodologies grounded in the NSD theory, which allowed us to treat flow as dynamic phenomena that changes and evolves over time, detecting different dynamical patterns in the within-individual fluctuations of flow. These NDS methodologies complement the conventional linear techniques by allowing researchers to previously diagnose whether they are faced with linear, nonlinear or random evolutions.

Likewise, our study also has certain limitations. For example, studies expanding on these results need to use a larger sample that includes a similar number of cases in each of the dynamic patterns. Although this lack of symmetry in terms of the cases representing each of the different patterns (75%, 20% and 5%) did not seem to affect our analyses (i.e., MCA), future research using larger samples should be conducted nonetheless. In addition, it should be emphasized that the present study also reveals a methodological limitation concerning certain sample bias due to the demands of the task required from employees (completing a diary several times a day over a period of 21 days). Given these demands, it is difficult to persuade poorly motivated employees to take part in such a study, and if they do, it is likely that their level of commitment will fall short of that required to complete the necessary entries

(100 recordings). Consequently, it may be interesting to study larger samples of employees with low levels of flow, with the aim of validating the findings obtained in the current study. Moreover, studying employees experiencing low levels of well-being may allow us to acquire valuable information regarding the dynamics of random and linear patterns over time, as well as the factors associated with them.

Moreover, it is important to examine possible limitations derived from the way we have measured flow. Although we use measures that are traditionally employed in flow research, we must emphasize the possible collinearity effects among the measures of challenge, skill (included in flow indexes 1 and 2) and their interaction term. Likewise, in the third measure of flow, the strategy of dichotomizing the two continuous variables of skill and challenge, may require more sophisticated analyses (e.g., cluster analysis) to determine whether employees are in a discrete, differentiable state of flow as proposed by the flow theory (Csikszentmihalyi, 1990). These limitations constitute the reasons why we have included three different measures of flow simultaneously in the present study. At any rate, we should emphasize that all three flow indexes correlate strongly. Likewise, the three indexes correlate highly with other correlates of flow including enjoyment, interest and absorption. Refining the construct validity of current measures of flow is beyond the main objectives of the present research study. It should undoubtedly be included, however, in the agenda for future research.

Future Research

The empirical results obtained in this study provide important clues for guiding future research on flow and employee well-being. First, it may be worthwhile to test and compare traditional explanatory models based on techniques of linear data analysis (e.g., SEM, HLM) with nonlinear models grounded in NDS data analysis (e.g., catastrophe models) to explain fluctuations in flow over time, and study which model fits the data best. Second, catastrophe models might be very useful for understanding the phase transitions as employees move into flow (chaotic dynamic) from other more negative states like apathy, boredom or anxiety (random or linear dynamics). These models have the capacity to explain the way in which continuous changes in the independent variable/s produce qualitative changes in the dependent variable/s; this is the reason why this methodology results appropriate for modeling discontinuous or abrupt changes (Guastello, 1995). As Schuldberg (2006, p. 563) states, "it will be worthwhile and fascinating to understand the dynamics and determinants of these phase transitions as people move into and out of what may be an optimal and desired state." Thus, catastrophe models may prove to be very useful for understanding the important discontinuous phenomena involved in employee well-being.

Third, chaotic patterns have a hidden order, which commonly features a relatively simple nonlinear dynamic system comprised by only a few variables. Future research on flow can build and run simulation models to search for the number of variables guiding the dynamic system. This may help to disentangle the number of variables needed to explain the experience of flow.

Conclusions

Although within-individual variability in employee well-being can behave in a linear way, there is increasing evidence in organizational research that it can also behave in a nonlinear or chaotic way. Identifying the latter type of intraindividual variability is important when it comes to choosing the appropriate techniques for data analysis and establishing our capacity for predicting the future behavior of well-being processes. Moreover, chaotic behavior appears to be associated with higher well-being. Hence, understanding the structure and behavior of chaos may provide a map of healthy functioning in organizations. In this sense, the NDS approach can complement classical linear approaches by offering new tools with which information that was formerly invisible becomes visible. Following the call by

Cameron, Dutton, and Quinn (2003) for the use of nonlinear models to study employee well-being, we hope that our findings stimulate research on the complex dynamics of flow and other forms of well-being, which will likely produce significant insights about employee flourishing.

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Table 1.

Means, Standard Deviations, and Correlations of Study Variables at Within- and Between-Persons Levels of Analysis

	M[a]	SD[a]	M[b]	SD[b]	1	2	3	4	5	6	7	8
1. Flow index 1	12.35	11.40	13.66	14.73		.650**	.461**	.627**	.185	.356**	.401**	.374**
2. Flow index 2	51.97	14.25	53.36	23.72	.639**		.741**	.908**	.148	.457**	.500**	.353**
3. Flow index 3	27.06	15.43	[c]	[c]	[c]	[c]		.738**	.004	.355**	.324**	.296**
4. Challenge	43.30	15.45	44.08	29.16	.593**	.913**	[c]		-.054	.349**	.442**	.212
5. Skill	77.53	12.21	78.18	20.3	.155**	.207**	[c]	-.066		.442**	.249	.533**
6. Enjoyment	67.38	13.34	69.04	25.78	.210**	.206**	[c]	.101*	.352**		.887**	819**
7. Interest	62.26	13.80	63.93	26.77	.298**	.353**	[c]	.273**	.241**	.778**		.728**
8. Absorption	68.91	14.60	70.31	25.11	.236**	.181**	[c]	.108**	.396**	.673**	.636**	

Note. Coefficients below the main diagonal reflect within-person correlations. To avoid overestimation of Pearson coefficients we have considered 10% of the total sample (698 logs across 60 participants). Coefficients above the main diagonal reflect between-persons correlations based on 60 participants.

[a] Between-persons level of analysis

[b] Within-persons level of analysis

[c] Flow index 3 was only estimated at the between-persons level of analysis

* $p<0.05$; ** $p<0.01$

Table 2.

Types of Dynamics Found in the Within-Individual Variability of Flow According to Different NDS Techniques.

First step: recurrence analysis		
Dynamical pattern	%	Number of cases
Linear	5	3
Nonlinear or random[1]	6.66	4
Chaotic	68.33	41
Random	20	12
Total series	100	60
Second step: surrogate data analysis		
Dynamical pattern	%	Number of cases
Linear	5	3
Chaotic	75	45
Random	20	12
Total series	100	60

[1] These cases correspond to those recurrence plots that were difficult to characterize as chaotic or random (see comments regarding the limitations of this technique in the method section). In the subsequent analysis (second step: surrogate analysis) it was confirmed that all these cases presented a chaotic dynamic.

Table 3.

MCA Axes.

Axis	Singular value	Proportion explained	Cumulative proportion
1	0.53139	56.93	56.93
2	0.20655	22.13	79.06
3	0.10038	10.75	89.82
4	0.06085	6.52	96.34
5	0.02545	2.73	99.06