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Lost in Transition? Complexity in Organisational Behaviour – the Contributions of Systems Theories[**]

The article demonstrates the usefulness of concepts and methods from systems theories for Organisational Behaviour (OB). Diagnosing development areas in OB, especially the analysis of whole systems and the degree of operationalisation and formalisation of core constructs and assumptions, the article uses the complexity hypothesis in career research to illustrate the opportunities and limitations of concepts and methods from systems theories. Finally, the consequences of such an approach for OB are discussed.

Key words: **Nonlinear Systems, Synergetics, Research Methods, Career Research**

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1. Introduction

Theoretical and empirical research in Organisational Behaviour (OB) has been quite successful: the discipline has its own identity despite cutting across various "traditional" scientific disciplines, for some phenomena like work motivation or group work the insight is considerable and last but not least, the topics that are the traditional focus of OB receive unbroken attention from the academic as well as the practitioners' world.

Yet a growing uneasiness about some developments or, in other parts, a lack of development starts to grow. The following elements could be seen as potential deficiency areas where new developments are needed: the current emphasis on individuals in organisations while neglecting larger social units or the organisation itself, the lack of attention to the temporal aspects, dynamics and complexity of OB phenomena in general and larger social systems in particular, and a scarcity of research methods that can be applied to dynamic systems.

While these shortcomings are well known for some time, there have been a number of attempts to make use of theories and methods that have been developed in other disciplines dealing with complex systems. Chaos theory is a good example for such attempts.

Apart from a steady interest in non-linear models in the area of economics (e.g., stock market modelling) the frequent use of chaos theory or related concepts in management literature or publications on organisational behaviour in the 1990s did not sustain. Concepts like fractal manufacturing or fractal companies (Warnecke 1993), strategic approaches at the edge of chaos (Brown/Eisenhardt 1998), organisation as flux and transformation (Morgan 1997) and others are largely metaphorical (for an overview see Stacey et al. 2000), and sometimes mostly rely on technical terms the authors use to impress the reader (Sokal/Bricmont 1998). Additionally, many concepts referring to chaos management and pretending to be directly derived from "new science" are after all just old wine in new bottles. Nonetheless, as Allan Sokal (1998) observed, many authors hold "forth at length on scientific theories about which one has, at best, an exceedingly hazy idea. The most common tactic is to use scientific (or pseudo-scientific) terminology without bothering much about what the words actually mean" (20). Furthermore, empirical research using chaos theory in the field of organisational behaviour never really existed.

This paper tries to contribute to potential development areas in OB in terms of theoretical foundations and research methods by pursuing three goals.

- First, the paper presents the basic concepts of a theory family holding promises to remedy some of the deficiencies in OB diagnosed above.
- Second, it describes some methods used within the scope of these theoretical concepts.
- Third, it will demonstrate the potential usefulness of these theoretical concepts and methods by applying them to empirical research in the area of managerial careers.

The "common denominator" of the threefold purpose of this paper is the focus on the complexity of systems which is an integral part of many OB phenomena at all levels of analysis.

2. Theorising about complex systems

More than one hundred years ago the French mathematician Henri Poincaré took a first glance on a complex dynamic we are now calling deterministic chaos. In 1889 he discovered – upon attempts to solve the problem of three interacting bodies by means of the Newtonian laws of gravitation – that even tiny errors or deviations in initial conditions produce vastly different outcomes. What is generally regarded today as an enormous merit of Poincaré bothered him considerably when he made his discovery:

> "...it may happen that small differences in the initial conditions produce very great ones in the final phenomena. A small error in the former will produce an enormous in the latter. Prediction becomes impossible, and we have the fortuitous phenomenon" (Poincaré 1908 cited from Peterson 1999)

It was not before the 1960s that this discovery by Poincaré was thoroughly understood and in some cases re-discovered (Lorenz 1963). Today phenomena like nonlinear phase transitions, self-organisation, butterfly effect, fractal geometric structures and others are well established concepts in natural science. Apart from a widespread and not very well-defined pool of theories like complexity theory (for an overview see e.g. Mainzer 1994; Mainzer 1999), the theory of dissipative structures (e.g. Prigogine 1955; Prigogine 1987), synergetics (e.g. Haken 1990; Haken/Wunderlin 1991), the theory of nonlinear dynamical systems (for a mathematical overview see Anishchenko et al. 2002), or chaos theory (e.g. Li/Yorke 1975; Schuster 1995), all of these concepts (for a detailed and commented list of references see Hilborn/Tufillaro 1997) deal with the complex behaviour of a special class of systems. In contrast to a system behaviour controlled from outside, they all focus on the self-organising dynamics of systems far from thermodynamic equilibrium.

The perspective of the theories of dynamical systems fits much better to a lot of issues discussed in the area of organisational behaviour than classical linear models or even cybernetic approaches do. Furthermore, the methodological and theoretical assumptions of the theories of dynamic systems can also innovate empirical studies in organisational behaviour, leading to a better understanding of organised complexity (Willke 1989), a highly improbable but nonetheless quite frequently occurring phenomenon, not only in nature. While this is not the place to discuss differences and similarities between various theoretical perspectives in detail, it is necessary to define major constituents of our theoretical approach: the theoretical roots in synergetics coming from natural sciences, the notion of open systems, and the concept of self-organisation and phase transition, all of them linked to synergetics.

2.1 Synergetics

It was mentioned above that there is not just one but several theories trying to explain the behaviour of complex systems. Besides the rich discussion coming from social systems theory (see, e.g., Luhmann 1984; Kasper et al. 1999), most theories on dynamical systems from natural sciences and mathematics are highly compatible in their basic as-

sumptions and in their mathematical foundations. Still, a lot of differences can be found in terminology, main paradigm, and focus of interest. For many of them, synergetics provide a key point of reference.

Synergetics was introduced by Hermann Haken in the early 1970s, at first to explain self-organising phenomena occurring in a laser light source (Haken 1970). Based on a clear mathematical formalisation, self-organisation can be understood as a spontaneous spatial-temporal pattern formation on a macroscopic level. There are several rather simple systems, first described in physics and chemistry, showing such spontaneous pattern formation. One example is the laser light, a highly ordered emission of light with only one frequency despite being based on billions of light sources, namely the atoms of the laser material. In chemistry, the Belusov-Zhabotinsky reactions are well known examples of self-organising processes, first explained by Prigogine (e.g. 1955). Some of these chemical reactions lead to spatial patterns like coloured spirals or to a periodical colour-changing pattern (chemical clocks).

Synergetics cannot only be applied in natural science. It is also arguably the most appropriate theory to explain spontaneous transitions between human movement patterns (e.g. Haken 1992, for an overview: Jirsa et al. 1998), or to understand self-organisation in medicine (Glass/Mackey 1977; Mackey/Milton 1987; an der Heiden 1992) and clinical psychology (Tschacher et al. 1992; Schiepek/Strunk 1994), in perception (Haken 1979; Stadler et al. 1991; Haken 1996), cognition (Stadler/Kruse 1990; Stadler et al. 1996; Stadler/Haynes 1999), group (Langthaler/Schiepek 1996) and social processes (Weidlich/Haag 1983).

2.2 Systems characteristics

The definition of what can be interpreted as a system depends on the viewpoint of a chosen systems theory. While definitions differ in some aspects, a basic definition of a system can be given with respect to two components. First, a system is a unit consisting of elements, which in turn can be seen as units, too. Second, the elements of a system are related by interdependencies. According to this definition, a system is more than a mere collection of elements as there must be a structure of relations between the elements. In that sense a pile of sand is no system due to a lack of relations between the sand grains (although by assuming a special viewpoint one may even postulate relations between ordinary sand grains, see Bak et al. 1989; Bak/Chen 1991).

In a (quite popular) interpretation of the given definition one may argue that the whole universe is the one and only relevant system because everything is more or less directly related to everything else. But there is more to the term "system" than that: A system is a functionally closed unit, where the interdependencies between the elements in the system are quantitatively stronger and qualitatively more productive than the system's environment.

Starting from this minimal definition, different theories further narrow it down by focusing on special types of elements or on typical system structures. Cybernetics (Wiener 1948) for example emphasizes the importance of negative feedback while a vicious circle is based on positive feedback structures between the system's elements. Due to its mathematical underpinning, synergetics is based on a quantitative concept: elements are variables and the relations between the elements can be represented as

mathematical functions (Klir 1991: 4). Insofar, a system can be modelled by formalising the elements and their relations as a set of equations, i.e., an equation system.

But synergetics is not only interested in a system's structure formalised in mathematical terms, it is much more interested in the behaviour of such systems, so the equation systems are used to describe how the variables change their values over time. Synergetics therefore deals with differential equations over time. This is admittedly nothing that distinguishes synergetics from classical mechanics, where the motion of an object over time is also described by using differential equations. But despite being based on the very same mathematical underpinnings, classical mechanics leads to mostly trivial, purely deterministic, and easy-to-predict system dynamics. In contrast, synergetics provides insight into very complex processes: erratic, non-trivial, and sometimes not even predictable behaviour of systems. The main differences between classical mechanics and synergetics leading to the different behaviours are threefold: First, mechanical systems are limited by the second law of thermodynamics (for a more detailed overview see Uffink 2001). Although no energy gets lost in a closed system, it is gradually transformed into useless warmth and the system's behaviour dies down after a very short while. All movements of such systems are merely transitions on a straight way to the system's death. Therefore, these systems (all closed systems, actually) are not able to exhibit complex patterns of self-organisation. Synergetics, however, deals with thermodynamically open systems, where a permanent energy flow enables the system to develop complex self-organising behaviour. Second, the mechanical approach to systems mostly remains focused on an interplay of only two variables, which excludes the possibility of complex non-trivial system behaviour (e.g., Poincaré and the *three*-body-problem, see above). Third, interactions of variables in mechanical systems are in most cases limited to a one-way perspective, leading from one independent to one dependent variable. Synergetics, however, deals with feedback loops, where positive and negative feedback builds a system of circular causality.

2.3 *Self-organisation*

Synergetics shows that self-organisation is observable on a macro level of a system, where a formation in time or space can be observed as an ordered pattern. But these observable patterns on the macro level are determined by the behaviour of elements located at the micro level of a system. In a process of circular causality the micro level builds up the macroscopic pattern, which in turn forces the elements of the micro level to behave in a certain way so that they fit into the pattern. Before self-organisation sets in, there is a "tournament" of possible behaviours (modes). At this stage, the elements' behaviour in total is random. Put in an oversimplified way, every element does what it likes to do. The technical term for this random behaviour, where all possible modes may happen with equal probability, is "symmetry".

As soon as self-organisation starts, a radical change called "phase-transition" occurs – an avalanche-like process where a fractionally dominant mode progressively becomes the dominating pattern, forcing more and more modes into its behaviour. Haken (e.g. 1990) calls this process of forced ordering "enslaving": the order parameter, which is the behaviour occurring at the macro level, enslaves the behaviour of all elements. In other words, the symmetry between the possible modes is broken down

to one dominating pattern. This is called symmetry breaking. Such processes of spontaneous order formation are very common phenomena, e.g. in the context of group dynamics, where after a storming phase norming sets in (Tuckman 1965).

As mentioned above, self-organisation, which here means the development of an order parameter, can only occur in open systems (Prigogine calls them dissipative systems, Prigogine 1955), where a continuous energy flow through the system is possible. Such systems are provided with energy from their environment and are able to emit useless unordered energy (called entropy) back to their environment. The energy flow through the system is regulated by so-called control parameters. Self-organisation only sets in beyond a critical threshold of energy. Moreover, a system often has several energy thresholds, and every border crossing results in qualitatively different order parameters.

A lot of studies based on this framework has shown self-organisation in different fields of natural science like biological processes (e.g. Deutsch 1994), processes in the human brain (e.g. Freeman/DiPrisco 1986; Freeman 2000); but such pattern formation can also be identified in psychological processes (e.g. Stadler/Kruse 1990; Stadler/Haynes 1999). Self-organisation is a much more common phenomenon than one may expect. One example of self-organisation and phase transition that is very easy to reproduce involves simultaneous finger movements. While it is not very difficult to slowly move both index fingers parallel from the left to the right, increasing the speed produces a discontinuous transition in movement. Beyond a critical speed the finger movement switches to an anti parallel (symmetric) movement. This transition can be described as a phase transition. Mathematical models (HKB-Equation – Haken et al. 1985) are able to simulate this process and have stimulated some hypotheses and further experiments concerning the influence of critical fluctuations at the transition point. Processes of energy-induced phase transitions are possible explanations for phenomena in organisational behaviour, too. For example, if a company faces aggressive demands concerning profits by powerful investors, it may start to show a completely different behaviour pattern (e.g. communication, culture, basic processes), even without undergoing any structural changes. Like phases in synergetics, such patterns are often fairly resistant against fluctuations or direct interventions, as is evidently described by Lewin (1997/1948/1951), who sees phenomena like phase transitions as a process where a stable pattern has to be "unfrozen" first, and a new, changed pattern has to be "refrozen" afterwards (cf. Beisel 1996).

Spontaneous order formation and symmetry breaking are a key feature in human perception, too. Human perception is not a passive projection of stimuli into some areas of our brain. It has much more of an active self-organising process, by which the percept is built up in mind, sometimes by using stimuli more as a perturbation than as a given fact. Figure 1 illustrates how the perceptive system fails to identify a stable pattern as it is unable to reach a final symmetry breaking. Gestalt psychologists of the early 1920s already proposed many laws as to how the human perception "invents" the outer world instead of simply reproducing it – synergetics' approaches to perception can be seen as a methodical as well as theoretical enhancement of these concepts. The idea that perception is not just a trivial but rather a highly complex process of a self organising system which can hardly be put down to simple rules is also supported by studies that have shown that many medicine students are very good at citing the

rules of how to interpret an X-ray picture but fail when actually asked to do so. On the other hand, experts with years of experience are extremely skilled in interpreting X-ray pictures, but if asked about their methodology, their explanations will be mostly rubbish. Despite their high level of skill, they do not know any more how they do it (Stadler/Haynes 1999).

Figure 1:   **Instability in the visual perceptive system**
(Figure from: Stadler/Kruse 1990 1990: 36)
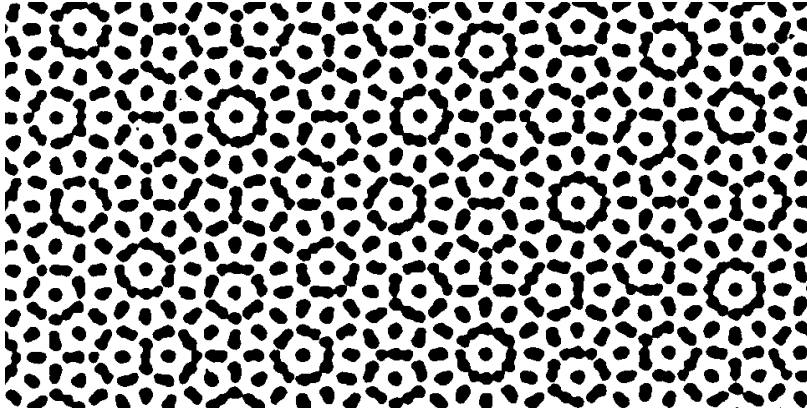
2.4 Phase transitions

The qualitative shift in order parameters occurring after a crossing of an energy threshold is called a phase transition (in mathematics phase transitions are termed bifurcations). Among others, four aspects of phase transitions are very interesting:

First, phase transitions are radical qualitative changes in temporal pattern formation occurring in the same system without structural changes. This means that one system often has the potential to generate many different behavioural patterns by self-organisation. Therefore, one explanatory model (which need not even be very extensive) is able to describe various operation modes of a system.

Second, phases that are far from a transition point form a stable self-organised pattern, similar to the way a feed-back control system works, always checking and regulating its output towards a certain value. In such a state, the system is fairly resistant to external perturbations. Thus, self-organisation leads to the formation of a behaviour pattern (or several patterns) the system is attracted to. Accordingly, these "preferred" patterns are frequently called attractors.

Third, synergetics provides tools that are able to identify possible order parameters (attractors) for mathematical systems, whereas one empirical "real life" system may have a great variety of possible order parameters without the possibility to identify all of them. Therefore, a complete description of all potential states is not always possible for these systems.

Fourth, control parameters are specific yet unspecific (Schiepek/Strunk 1994) for the nature of a phase transition. On the one hand, they are necessary and therefore a

specific reason for a transition. On the other hand, the preferred behaviour patterns (attractors) on both sides of the energy threshold are self-organised order parameters of the system. The concrete behaviour is neither determined by the supplied energy nor by changes in the control parameters, but by the system itself. Therefore, a control parameter has no specific influence on the concrete manifestation of a system's behaviour.

2.5 Illustration: Self-organisation, perturbation and enslavement

Using an example from language can illustrate various aspects that have been addressed above, especially the self-organised interplay of micro and macro level (see Haken 1979: 8).

The following letters make no sense at all when read as a word or sentence:

a, a, h, i, i, m, n, s, s, t

These letters can be seen as elements of a system (the micro level), and by rearranging them we can find out about the system's degrees of freedom. If the letters were written on dice and put into a box, we could get many different combinations by shaking the box and emptying it onto a table several times. Although the process of shaking and shuffling can be seen as a control parameter, no self-organisation takes place. It might occur momentarily that the dice are arranged in a way so that the sequence of letters makes sense, but the next shake immediately destroys this meaningful sequence. In this scenario, there is no system at all, as there are no interdependencies between the letters. On the other hand, given the same letters in scrabble one is able to arrange the letters to form sentences like the following:

"this is a man"

On the micro level nothing has changed, there is just another arrangement of the letters, which is but one of a whole lot of possible arrangements. The difference lies in the macro-level pattern, which now makes sense. The letters have acquired a new quality, an order parameter. The scrabble player, who knows about relationships between the letters, and operates in interplay with the letters as a feedback control system, (hopefully) produces an entirely different result compared to the sequences obtained by simply shaking the dice.

At the very beginning, many modes are possible. The player may first arrange the word "man" and if she likes it, this mode becomes dominant in the sense that it limits the degrees of freedom for the remaining elements of the system, making the order parameter show its effect step by step. But there are other meaningful arrangements than the one above, such as:

"is this a man?"

This new sentence illustrates that the same system is able to produce different order parameters. Both sentences are built by the same letters (even the same words, actually), but two equally sensible outputs may be produced just by deciding in favour of one of them. This phenomenon is called symmetry breaking. Every time a system finds itself "at the crossroads" and must opt for one among several equally attractive possibilities of future behaviour, the symmetry between the opportunities must be broken. The outcome of this is frequently determined by random ("I haven't got the

faintest idea where I'll end up with that, but I'll just try X"). A system at such a point "just before the crossroads" is called critically instable. In its history, a system passes an enormous amount of such "junctions", so the way the system develops in time becomes more and more an interplay of random fluctuations and self-ordering and cannot be predicted. Therefore, such systems build up their own "private" history.

Apart from order parameters and states of critical instability, this example may also be taken to illustrate the resistance of a system against minor perturbations. Once the sense of the sequence is obvious to us, even small perturbations (such as a misprint) won't force the scrabble player to get back to square zero or start with random sequences again. Furthermore, once the meaning of the sentence is known, the arrangement of the letters is only a consequence. The macroscopic order parameter (perceived meaning of the sentence) "enslaves" the process of arranging the letters.

3. Organised complexity

The former sections were an attempt to describe some basic concepts in synergetics, focusing on the mechanisms that lead to phenomena of self-organisation, especially the processes of circular causality between the behaviour of elements on a micro level and the collective system behaviour. However, the patterns of behaviour themselves, which complex self-organised systems may exhibit, have not yet been addressed.

Self-organisation on the level of a system's behaviour means the formation of organised dynamic structures, i.e., of ordered patterns. While simple, easily predictable behaviour is a characteristic of trivial systems, self-organisation becomes manifest by highly complex yet ordered behaviour patterns.

The sequence of letters "this is a man" appears much more complex than the alphabetically sorted "original" sequence. The sequence of symbols of which this article consists is highly complex, and this is what makes this article appear meaningful and organised. Sorting the letters of this text alphabetically would result in a scarcely complex and trivial pattern that could as easily be produced by a simple program and any PC as a random shuffling of the letters. It is the well organised but nonetheless complex sequence of letters, "between" a random sequence and a trivial, simple one (consisting of the same elements!), that gives evidence of an "intelligent", purposeful process of self-organisation. The distinction between random, trivial and complex order is the core concept of empirical research about self-organisation, which shall be addressed in the following sections.

3.1 Conceptual foundations

The most popular issue in modern system theories is so-called deterministic chaos. Deterministic chaos denotes a (seemingly) random behaviour occurring in a deterministic system (Stewart 2002: 12). Chaos appears to be random because there is no evident order in what a chaotic system does, like there seems to be no order in the successive decimal places of the square root of two (1,4142135623730950488016887242097…). Additionally, in a chaotic dynamic no periodicity can be found (just as there is no recurring periodicity in the square root of two), which suggests a complete lack of rules and patterns. But chaos is actually all but without a pattern, because it is the dynamic behaviour of a deterministic system; just as the square root of two is not a random

number but strictly determined. Chaos is a complex form of dynamics – much more complex than simple periodic rhythms, but nevertheless it follows a certain order and is therefore far from being random. Deterministic chaos is actually a very common self-organised behaviour.

Apart from the features of deterministic chaos already mentioned, chaos is best defined by the so called butterfly effect. Even very small differences between two possible actual states of a chaotic system increase exponentially in time, which makes it impossible to predict the behaviour of a chaotic system for a longer period of time. Nevertheless, the system does not alter its basic pattern. To give an illustrative example: it is the interplay of such small fluctuations and a chaotic system that forms the differences in the shapes of plants, too – the leaves of a certain plant species are often largely different in detail but are nonetheless similarly shaped.

However, chaos is only one possible behaviour of a special class of systems. First, chaos can only be found in systems far from thermodynamic equilibrium. This is true for all living systems and also for many non-living systems. Second, chaos is based on the interplay of more than two variables. While positive feedback systems are vicious circles, and negative feedback systems are the core of an equilibrium system, chaos is based on mixed feedback (an der Heiden/Mackey 1987). Finally yet importantly, there must be at least one mathematically non-linear term describing the relation between the variables. Systems built up only by linear interactions are not able to behave chaotically. All in all there are only few requirements for a chaotic motion. Therefore, chaos is quite likely to be found in various systems.

Sometimes in popular management literature, chaos is valued as undesired and problematic. Nevertheless, seen from a theoretical standpoint, chaos is the only dynamic which is adaptable and flexible (due to the butterfly effect), without totally losing its pattern. Organisational change processes, learning organisations and organisation flexibility in the context of new organisational forms are only understandable in the context of self-organisation. Neither a feedback-control-system nor a classical mechanical system is able to adapt its behaviour. Also in medicine, the search for chaos shows that health is linked to chaotic processes and not to regularity. Within certain limits high heart rate variability, for instance, (in contrast to a rigid periodicity) is a very good predictor for the positive outcome of cardiac diseases (Skinner et al. 1990). The heart rate has to be adaptable and flexible on the one hand to respond to changing environmental requirements, but on the other hand it must have a functional pattern that ensures, e.g., a good coordination of the heart muscle contractions. In addition, chaotic processes dominate the EEG of an awake person (Pritchard/Duke 1995), and a reduction in complexity is often linked to illnesses like epileptic seizures (Sackellares et al. 2000). On a socio-psychological level, chaos plays a fundamental role in adapting, innovating and negotiating the complex patterns of interactions in working groups (Schiepek et al. 1995a; Schiepek et al. 1995b).

Synergetics offers a concrete and applicable framework to handle other dynamical patterns beyond chaos, too, and to explain the transitions between such patterns. As far as the interest in organisational behaviour is associated with the characterisation and understanding of processes, theories on dynamical systems, such as synergetics, are very potent frameworks to cover all aspects of organised complexity.

However, empirical research in the field of complex systems often faces limitations rooted in the system's behaviour itself. For example, it is very hard to answer even easy questions like the one concerning the similarity of two given dynamics. In the case of chaotic behaviour, this question cannot be answered by linear correlation. Because of the butterfly effect even the dynamics of completely identical systems diverge exponentially.

Methodologically, there are two basic approaches to research in the field of dynamical systems. One approach (bottom-up-method) takes a "real-life" system as a starting point and attempts to describe its behaviour by selecting, operationalising, and measuring the relevant variables and parameters (put in a very simplified way). The other approach starts from theory and uses mathematical formalisation to build an equation system. Mathematical analysis and computer simulations of the equation system's behaviour then give insight into the self-organising processes. The latter "top-down" approach is typical for synergetics, introduced by Hermann Haken (e.g. 1990).

Both these methodological approaches (bottom-up and top-down) are bound to very specific methods and algorithms (for an overview on bottom-up methods see Hegger et al. 1999; Schreiber 1999) and both aim at generating time series containing complex dynamic patterns (cf. Schiepek/Strunk 1994). Ideally, top-down and bottom-up approaches are both used for a reciprocal comparison (see Figure 2 adapted from Schiepek/Strunk 1994: 95). Nevertheless, approaches using either the way of theoretical modelling or the way of time series analysis are rewarding as well. In the following section we will give a brief description of some methods for nonlinear time series analysis.

3.2 Algorithms to measure complexity

Theories on dynamical systems offer a broad spectrum of statistical and mathematical tools in order to obtain precise quantitative measurements of complexity, order, determinism, and chaoticity. Most of these algorithms have been developed in the last 20 years, frequently based on older precursors. In the following section we will give a brief overview over five different methods. The first three of them are relatively easy to implement and can also be applied with nominal data. The fourth algorithm represents a class of complexity measurements based on the concept of fractal geometry. The fifth class of algorithms presented here are quantifications of the chaoticity of a process:

1. *Classical Information Theory:* One standard method to determine the complexity of a sequence of events or symbols is Shannon's definition of the information content (Shannon 1948). According to this definition, the information content of a sequence of values is equal to the sum (over all values) of the probability of the appearance of one value, multiplied with the logarithm of this probability:

    Equation 1: $I_s = -\sum_{i=1}^{N} P(s_i) \ln P(s_i).$

    Consequently, the information content of a series of symbols can be calculated by its frequency distribution. For the sequence "this is a man", the information content can quite easily be calculated according to Equation 1 and amounts to 1.89.

Figure 2: **Systemic Methodology** (Adapted from Schiepek/Strunk 1994: 95f.).
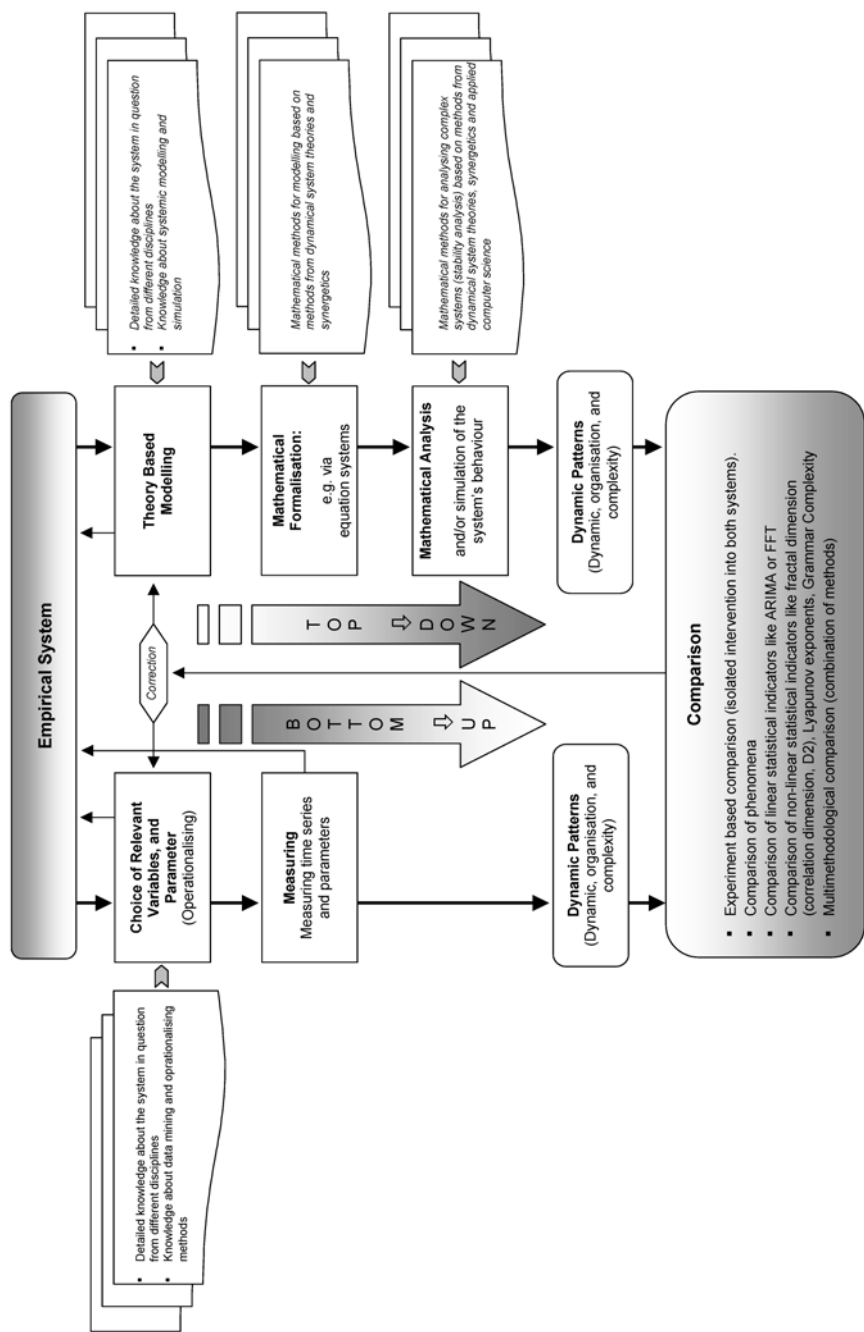
In contrast, the equally long but less complex sequence "th th th th th", yields a value of only 0.7, due to the redundancies in the latter series. Although Shannon's equation is one of the most widely used measurements on information content, it has some se-

rious shortcomings, one of the most important lying in the fact that any sequence containing the same symbols as the example presented above yields the same result. So, "this is a man", and "I mash satin" have the same information content.

2. *Symbol Dynamics:* Because of these shortcomings of classical information theory concerning an accurate measurement of the complexity of ordered patterns, we face the question of how the idea of information content can be extended to taking the ordering of a symbol sequence into account. One solution proposed for this problem is the so-called symbol dynamics concept (for an overview see Collet/Eckmann 1980), which is originally based on Hadamard (Hadamard, 1898), and was enhanced by Hedlund and Morse (Morse 1921; Morse/Hedlund 1938). Symbol dynamics offers a set of different methods to deal with organised complexity. A common one is to build up a frequency distribution not only for single symbols but for so called *words*, consisting of a given number of m symbols. With $m = 2$, the sentence "This is a man" can be broken down into nine two-letter "words": "Th, hi, is, si, is, sa, am, ma, an". Afterwards, equation 1 can be used to calculate the information content using the relative frequency of the words. For longer series of symbols, this approach produces different information content values for the given series ("This is a man"), its sorted variant ("a a h i i m n s s t"), and a randomly shuffled version ("a t s i m a s i n h"). But information content depends on the length of a word, so it is useful to restart the calculation with larger m (including more letters). If a series is sufficiently long and one can find no significant difference to an equal distribution of the relative frequencies of words for different m, the series is probably the result of a random process (such as shaking dice in a box, see above).

3. *Algorithmic Entropy:* The fundamentals of algorithmic entropy are based on work in the field of algorithmic information theory (Kolmogorov 1965; Zvonkin/Levin 1970; Chaitin 1974), which determines the information content of a sequence of symbols by the information content necessary to completely describe the sequence. The square root of two, for example, is a number with infinitely many decimals that produce an extremely complex sequence of digits. Nonetheless the square root of two can be calculated using simple algorithms. Algorithmic information theory is based on these ideas, assuming that a rather simple algorithm is able to describe complex structures. Sequences that show patterns of ordered complexity can normally be put down to simpler algorithms, but in the case of a random sequence, the necessary algorithm is just as complex as the sequence itself, and maximum algorithmic entropy is attained (Hubermann/Hogg 1986).

Software that is used for file compression works on a similar basis – the compressed file is an algorithm that is able to reproduce the original file. The ratio of compression indicates how ordered the original data are. Random data can not be compressed, whereas highly ordered series of symbols are very suitable for compression. The so-called Grammar Complexity is an example for such a compression algorithm (Jiménez-Montano 1984; Rapp et al. 1991). One way of interpreting results from Grammar Complexity consists in generating many sequences that consist of the same elements as the original sequence but are randomly shuffled. The Grammar Complexity values for these surrogate series are normally distrib-

uted, allowing testing the complexity of the original sequence against that of the random surrogates. Unlike Shannon's algorithm presented above, the Grammar Complexity does differentiate between more and less ordered patterns.

The Grammar Complexity procedure has already been employed successfully in social sciences (e.g. Rapp et al. 1991; Tschacher/Scheier 1995). Its shortcomings are that both the length of the examined sequence and its distribution of values influence the results. Along with Grammar Complexity, other algorithms have been proposed that are also based on methods of data compression (for a comparative overview, see e.g. Schürmann/Grassberger 1996).

4. *Strange Attractors:* It was in 1971 when Ruelle and Takens termed the complex structure of a chaotic attractor strange attractor. Its geometric properties are very different from well shaped Euclidian forms (such as circles, squares, cubes etc.). It is the concept of fractal geometrical forms, introduced by Benoît B. Mandelbrot, which helps to handle such complex, "broken" but nevertheless ordered structures. Ruelle and Takens postulate that whenever an attractor can be shown to be a fractal, the underlying system is chaotic.

The basics of fractal geometry (e.g. Mandelbrot 1987) were already formulated early in the 20th century by mathematicians like Hausdorff and Besicovitch (Hausdorff 1919; Besicovitch/Ursell 1937) and are based on concepts of a body's dimensions. The following example shall illustrate the basic concept: in order to measure the length of a straight line with an item (e.g. a ruler) that is only half as long as the line, the item will have to be applied twice (three times respectively if the ruler is only a third as long as the line, etc.). In order to determine the area of a square with a side length of k by using a square with a side length of $k/2$, one would need four such squares to cover the whole area of the former square. Applying the same principle in order to determine the volume of a cube with a side length of k by smaller cubes with a side length of $k/2$, one would need eight such cubes to "fill" the original cube. If the side length of the "measuring" items were $k/3$, one would need nine squares and twenty-seven cubes respectively. So if the length (or side length) of the original form is x times the length of the "measuring" item, one needs x^1 items to measure length, x^2 items to measure area, and x^3 items to measure volume. The exponent thus always corresponds to the dimensionality of the object in question. However, this is *not* the case for a fractal, as Mandelbrot has shown by using the example of a coastline. If one measures the length of a coastline with a "long ruler" (i.e., one that spans the beeline between two points), then breaks the ruler into x smaller pieces and measures the length of the coastline (not the beeline distance between the two points) again, one will "run out of ruler" way before the end point is reached, due to the complex structure of the coastline that "unfolds" as the ruler pieces used to measure the length of the coastline become shorter. The number of pieces necessary to measure the length of the coastline is therefore larger than x, but remains smaller than x^2. The dimensionality of the coastline is therefore higher than that of a line but lower than that of an area (and therefore obviously not an integer number). The more complex and jagged the coastline, the higher its dimensionality. Put in a very sim-

plified way, whenever a form has a higher dimensionality than would be expected and its dimensionality is not an integer number, it is a fractal.

A successful determination of the fractal dimension of an empirically given dynamic allows drawing the following conclusions: First, the higher the fractal dimension of a dynamic process, the higher its complexity. Second, if the fractal dimension of a process derived from empirical data can be determined, the process in question is not a random process (random has no structure at all). Third, the fractal dimension rounded up to the next integer number specifies the minimum number of independent but interacting factors the system needs to generate its dynamics. Several methods have been proposed to determine the fractal dimension of a time series (e.g. Grassberger/Procaccia 1983b; Grassberger/Procaccia 1983a). What all these methods have in common is that they theoretically require an infinitely long time series for a reliable calculation. Even though about 1.000 sampling points are generally regarded as a small yet sufficient number for attractors of a low fractal dimension (for a controversial discussion about this topic see Tsonis 1992), this is still a hard requirement for behavioural science.

Another feature of this method is that it aims at generating a representation of an attractor in phase space. The term "phase space" stands for a coordinate system where the variables that affect the system (regularly the degrees of freedom) form the coordinate axes. However, there is only one time series available at the outset with which the phase space has to be constructed. A solution for this problem is provided by Packard and Takens (cf. Packard et al. 1980; Takens 1981), who proposed a theorem according to which the whole phase space can be reconstructed via one single time series. Their method is based on choosing a constant time lag (this method is therefore known as time lag reconstruction) that determines to which dimension each sampling point is assigned. The value of the first sampling point of the time series is assigned to the first dimension of the phase space. The value of the sampling point after one times the time lag is assigned to the second dimension, the value of the sampling point after two times the time lag is assigned to the third dimension, and so on. If the time lag is well chosen, the reconstructed attractor in phase space is topologically equivalent to the attractor of the underlying system. Several methods have been proposed to find an appropriate time lag for the reconstruction of the attractor (cf. Fraser/Swinney 1986; Tsonis 1992).

5. *Measuring the Butterfly Effect:* Since the work of Grassberger and Procaccia (1983b; 1983a) a lot of publications have shown the fractal structure of a broad variety of processes. But not all of them are actually chaotic. The calculation of fractal dimension still leaves some methodological problems, since it is an appropriate method of calculating the complexity of a time series, but not for the detection of chaos (e.g., due to the limited length of the time series). Measurements of chaos (or more precisely: chaoticity) are based on an operationalisation of the butterfly effect. Like for the fractal dimension of strange attractors, algorithms for calculating the butterfly effect are also based on a phase space representation of the time series in question. For every point in phase space an algorithm searches for the nearest neighbour. The difference between the reference point and the nearest

neighbour can be taken as the flap of a butterfly's wing. Chaos can be found by following the trajectories of the reference point and its nearest neighbour. If the system is chaotic the two trajectories diverge exponentially in time (butterfly effect). An algorithm of Rosenstein et al (1993) does this for each reference point, and if the "averaged butterfly effect" still shows an exponential divergence, the system's dynamic is chaotic. The exponent which describes the degree of divergence is called Largest Lyapunov Exponent.

4. The complexity of careers – an example

We would now like to demonstrate how the methods and theoretical assumptions of theories on dynamic systems are helpful not only in physics but also in organisational behaviour by presenting an example from career research where methods stemming from chaos research were applied to data on career paths.

4.1 Complexity hypothesis

While the field of activity of career research was until quite recently almost exclusively limited to careers within organizations (e.g. Becker/Strauss 1956; Super 1957; Glaser 1968; Hall 1976; Schein 1978; Gunz 1989), a different type of careers is now apparently gaining more and more theoretical as well as practical relevance. It is marked by numerous transitions between jobs, organisations, or fields of professional activity, a lack of institutionalised and "ordered" career paths and/or career rules, and the fact that it is almost solely up to the individual actor to take care of his or her career, with little or no external support. This results in a less stable, less predictable career path labelled for instance as "boundaryless career" (Arthur/Rousseau 1996), "protean career" (Hall 1996), "post-corporate career" (Peiperl/Baruch 1997), or "chronic flexibility" (Mayrhofer et al. 2000).

Regardless of one's enthusiasm for the idea of a radically changing career environment, common wisdom has it that careers nowadays are more erratic and diverse than they were several decades ago. This claim of increased career complexity can be labelled as "complexity hypothesis in career research". In spite of an increasing number of papers that postulate such an increasing complexity of careers, there is a lack of methodological as well as theoretical concepts that offer a sound operationalisation of the term "complexity" in career research. In addition, relating empirical research is largely missing. We have tried to bring career research and synergetics together by applying methods from non-linear time series analysis in order to investigate the two following questions:

1. *Are professional careers in the 1990s more complex than they have been in the 1970s?*
    This question addresses the issue of increased complexity of more recent careers compared to those that have begun earlier. It shall be shown that careers, conceived as dynamic processes, in a strict and mathematically formalised sense are indeed more complex in the 1990s than they have been in the 1970s.

2. *Are these "new careers" complex or random processes?*
    If "new careers" turned out to be random processes without any order, any theory to explain these career paths would be useless. It shall therefore not only be analysed whether careers have become more complex, but also whether they are deterministic and therefore distinct from random processes.

4.2 Sample

Empirically, we use data from the Vienna Career Panel Project (ViCaPP). Since 2000, ViCaPP has collected data on the careers of Austrian business school graduates. The analyses are based on the first 13 career years of 95 graduates who completed their studies around 1970 and 120 graduates who did so around 1990. Based on a curriculum-vitae-like list of professional activities for each person, their professional development was charted for each year since their graduation along several variables with a sampling frequency of one year. The following analyses are based on five time-series per person, representing her/his career patterns in time. Based on Mayrhofer et al. (2000) three of the five variables are based on a concept named the coupling dimension (how tightly linked and mutually dependent actors are in their career-related actions and decisions) of career field theory. Coupling was operationalised by the following three items:

- Security and calculability of career-related prospects (very secure vs. very precarious).
- Subjection of career-related prospects to specific external actors and/or constraints (very dependent vs. completely independent).
- How easily another adequate job could be found should the need arise (very easily vs. not at all).

The other two time series refer to instability and variation in actors' professional relationships and job content. This concept is also based on Mayrhofer et al. (2000) and is called the configuration dimension. Configuration was represented by the following two items:

- Stability of work content (very stable vs. ever-changing)
- Stability of professional relations (very stable vs. ever-changing)

A factor analysis results in a two-factor solution (as proposed by the underlying theory), which explains about 60% of the total variance.

4.3 Methods from systems theories

Before applying two of the methods from chaos research presented above, the two research questions shall briefly be discussed from a "traditional" methodological standpoint, showing the potential as well as the limitations of consuetudinary methods.

For example, career complexity could also quite easily be assessed by calculating the means of the items measuring configuration. These results actually suggest that the persons from the 90s cohort report less stability concerning both work content and professional relationships. However, effect size is only marginal (3% of variance explained) and becomes significant solely due to the large n (annual measurements over 13 years times 215 participants). The other three variables do not actually address career complexity, making their mean values appear of little benefit. Another possible approach would consist in taking the changes in standard deviation as an indicator of increasing or decreasing career complexity. However, these results show that for three out of the five variables the standard deviation is larger in the 70s cohort than in the 90s cohort. But finally neither mean value nor standard deviation tell us anything about whether the career paths of the two cohorts differ concerning order and complexity from a dynamical perspective.

Two methods already discussed above stemming from chaos research have been applied in order to analyse the complexity of the collected data on career paths. On the one hand, the dynamic complexity of the career paths regarding hidden structures, such as recurring patterns, is analysed via Grammar Complexity (Jiménez-Montano 1984; Rapp et al. 1991). On the other hand, a method for the determination of fractal dimension of time series is used (Grassberger/Procaccia 1983b; Grassberger/Procaccia 1983a).

Algorithmic Entropy – Grammar Complexity

Two indicators were calculated for each person in order to analyse the algorithmic entropy. The first one is the quotient of the Grammar Complexity value of the original time series divided by the Grammar Complexity value of the same time series sorted in ascending order. The higher the quotient, the more complex the observed sequence.

The second indicator is based on the test of surrogate sequences already outlined above. The Grammar Complexity value for the original sequence is compared to a distribution of Grammar Complexity values for 200 randomised surrogate sequences consisting of the same elements.

Correlation dimension

Contrary to Grammar Complexity, correlation dimension – coming from fractal geometry and related to the discussion about strange attractors – makes use of the additional information provided by interval scaled data, compared to nominal symbol sequences. However, it has stricter standards concerning the required length of the examined time series, which also depends on its complexity. While several hundred sampling points are sufficient for moderately complex time series, highly complex systems require several thousand sampling points for this method to be applied.

Therefore, the individual time series were added up here to form a quasi-time series of sufficient length. In order to examine whether the specific complexity found for this resulting time series is actually due to the dynamics of the process and not to the order in which the original time series were added up, 100 (differently assembled) quasi-time series were examined for each cohort.

One crucial feature of this method is the distinction between a chaotic and a random process – the latter can be clearly identified by an infinite fractal dimension. Accordingly, a finite fractal dimension for the quasi-time series (in different "assemblies") would imply that the time series are deterministic (and that the process dynamics for the single persons are quite similar). In order to simplify the calculation, just the two underlying dimensions (coupling and configuration) are used as sources for the quasi-time series by taking the means of the two and three items assigned to configuration and coupling, respectively.

4.4 Results

Increasing complexity?

The results for the first indicator, the mean quotient Grammar Complexity values for the two cohorts, are presented in Figure 3 and Table 1. It is apparent that the values

scarcely exceed the theoretical minimum of 1, which is largely due to the limited sensitivity of this method in the case of short symbol sequences (cf. Rapp et al. 1991).

Figure 3: **Grammar Complexity quotient for the two cohorts and observed periods**
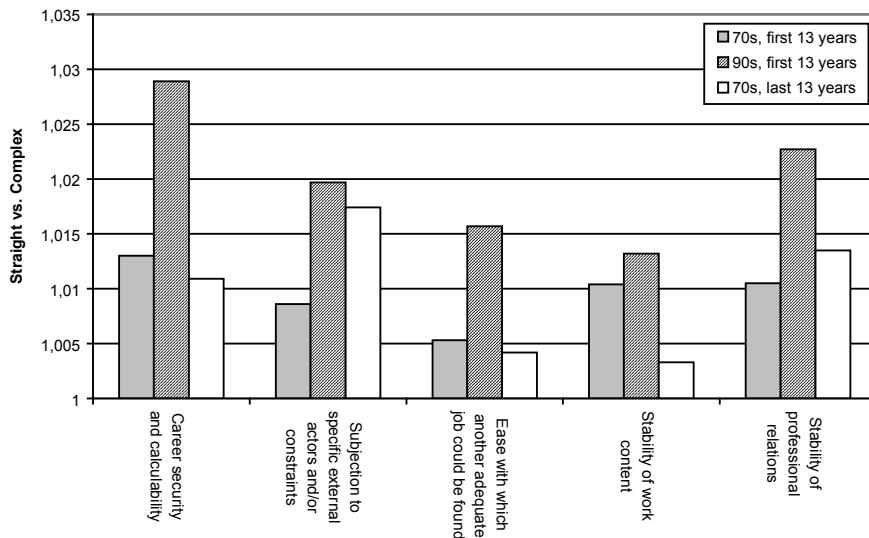
Table 1: **Comparison of the Grammar Complexity quotients**

Straight vs. Complex		70s cohort			90s cohort			
Dimension	Period	mean	standard deviation	N	mean	standard deviation	N	T-Test (1-tailed)
Coupling				95			120	
Career security and calculability	*First 13 years*	1.0130	0.0391		1.0289	0.0721		*
	Last 13 years	1.0109	0.0397		*last 13 years 70s vs. first 13 years 90s*			*
Subjection to specific external actors and/or constraints	*First 13 years*	1.0086	0.0344		1.0197	0.0552		*
	Last 13 years	1.0174	0.0517		*last 13 years 70s vs. first 13 years 90s*			ns
Ease with which another adequate job could be found	*First 13 years*	1.0053	0.0270		1.0157	0.0518		*
	Last 13 years	1.0042	0.0197		*last 13 years 70s vs. first 13 years 90s*			*
Configuration				95			120	
Stability of work content	*First 13 years*	1.0104	0.0418		1.0132	0.0485		ns
	Last 13 years	1.0033	0.0211		*last 13 years 70s vs. first 13 years 90s*			*
Stability of professional relations	*First 13 years*	1.0105	0.0413		1.0227	0.0595		*
	Last 13 years	1.0135	0.0425		*last 13 years 70s vs. first 13 years 90s*			ns

* p < 0.05   ** p < 0.01

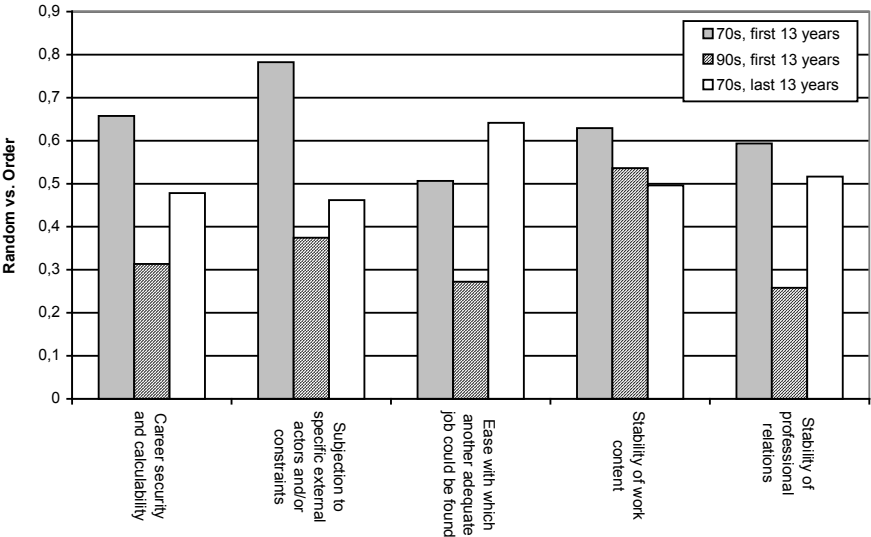**Figure 4:**   **Mean Grammar Complexity values after z-transformation for both cohorts**

Table 2:   **Comparison of the mean Grammar Complexity values after z-transformation for both cohorts**

Random vs. Order		70s cohort			90s cohort			
Dimension	period	mean	standard deviation	N	mean	standard deviation	N	T-Test (1-tailed)
Coupling				95			120	
Career security and calculability	*First 13 years*	0.6575	0.9895		0.3136	1.0791		**
	Last 13 years	0.4784	0.8535		*last 13 years 70s vs. first 13 years 90s*			ns
Subjection to specific external actors and/or constraints	*First 13 years*	0.7826	1.0212		0.3745	0.9646		**
	Last 13 years	0.4618	0.8445		*last 13 years 70s vs. first 13 years 90s*			ns
Ease with which another adequate job could be found	*First 13 years*	0.5068	0.7862		0.2722	0.9853		*
	Last 13 years	0.6417	0.9409		*last 13 years 70s vs. first 13 years 90s*			**
Configuration				95			120	
Stability of work content	*First 13 years*	0.6295	0.9946		0.5366	1.1797		ns
	Last 13 years	0.4964	0.9305		*last 13 years 70s vs. first 13 years 90s*			ns
Stability of professional relations	*First 13 years*	0.5936	0.9301		0.2581	1.0540		**
	Last 13 years	0.5165	0.9087		*last 13 years 70s vs. first 13 years 90s*			*

    *   p < 0.05   ** p < 0.01

Despite all these limitations, the 90s cohort has higher complexity values on all five scales, both when compared to the first and last 13 working years of the 70s cohort. For the comparison of the first 13 career years of both cohorts, all observed differences but one (stability of work content) are statistically significant. The results of the calculations of algorithmic entropy suggest that the career paths are indeed more complex for the 90s cohort than for the 70s cohort. However, these results should be accepted with caution, as the test power of the method employed here is rather poor due to the extremely short sequences consisting of merely 13 values.

The results for the second indicator based on the test of surrogate sequences are presented in Figure 4 and Table 2. They show the means of the z-transformed Grammar Complexity values for both cohorts. The higher the value, the more ordered the underlying sequence, compared to a random sequence. Additionally, z-values larger than 1.96 indicate that the observed sequence is significantly more ordered than a random sequence. It is apparent that the results for both cohorts fall short of this value.

Overall, the first indicator suggests that the observed career paths are at least a bit more complex than their "most ordered" variant, while the second indicator implies that the complexity found in these career paths does not clearly distinguish them from a random process. Although both indicators are basically in accordance with the "complexity hypothesis in career research", they both yield rather dissatisfactory results. On the one hand, the observed sequences only show a very limited complexity, on the other hand this limited complexity is not clearly distinct from a random process.

Random or complex?

Figure 5 shows the two-dimensional embedding for a randomly chosen variant of each of the three time series. As was already found for empirical data in social sciences, but also in medicine (e.g. Schiepek et al. 1997), no clearly structured attractors could be identified, as opposed to mathematically generated time series.

A simple order structure cannot be identified with the naked eye, nevertheless the phase space embedding for the 90s cohort appears more complex than that for the 70s. This may (partly) be due to the fact that more points were available from the quasi-time series for the 90s cohort than from the first and last 13 working years of the 70s cohort (1,560 vs. 1,235 points). Examining the results for the 70s cohort only, it is also apparent that the representation for the last 13 years looks less complex than for the first 13 years, with the number of points being equal for these two quasi-time series.

The calculations of the fractal dimension via an algorithm called correlation dimension (D2, cf. Grassberger/Procaccia 1983b; Grassberger/Procaccia 1983a) confirm this impression. As Table 3 shows, a finite fractal dimension could be attained for almost all variants of the three quasi-time series. For the first 13 years of the 70s cohort, only six variants out of 100 are not distinguishable from a random process. For the 90s cohort, the respective number was twelve. For the last 13 years of the 70s cohort, all 100 variants reached a finite D2 value.

**Figure 5:**   **Two-dimensional embeddings for samples of the three quasi-time series**
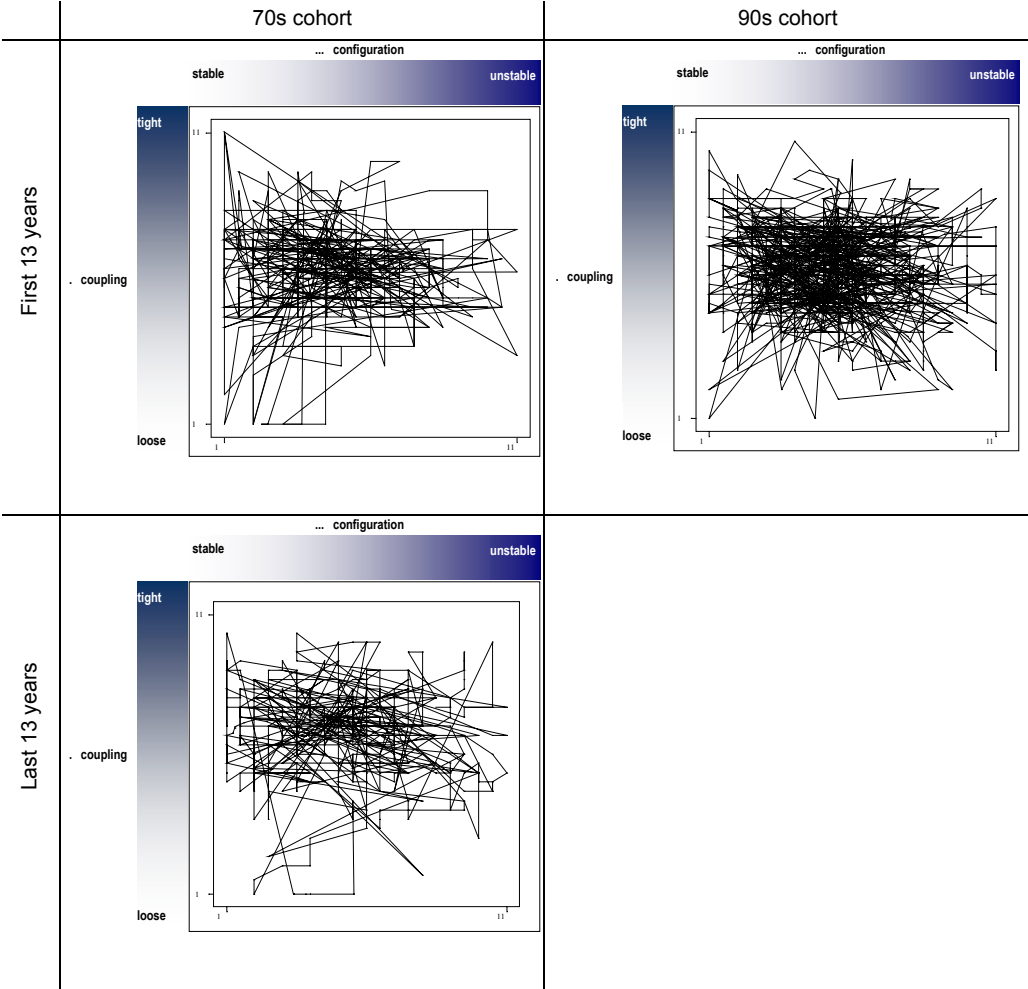
The small number of variants of the quasi-time series that did not attain a finite fractal dimension is quite astonishing. Much more clearly than expected, these results suggest that the career paths represented by the quasi-time series are not random processes. Rather, the results imply that career paths are complex, dynamic structures that can be put down to deterministic processes. Furthermore, there are only marginal differences between the results for the 100 different calculations which rarely exceed the error margin of calculation.

The D2 dimension for the 90s cohort is higher by about one dimension than that of the 70s cohort (see Figure 6 and Table 3). Consequently, while at least four interacting variables of a deterministic system are necessary to describe the career paths of the 70s cohort, the respective number for the 90s cohort is five. In addition, it is apparent that the system formed by the last 13 working years of the 70s cohort is less complex than the system formed by their first 13 years. This difference is much

complex than the system formed by their first 13 years. This difference is much smaller however than that between the cohorts.

Figure 6:   Correlation dimension (D2) of the three quasi-time series
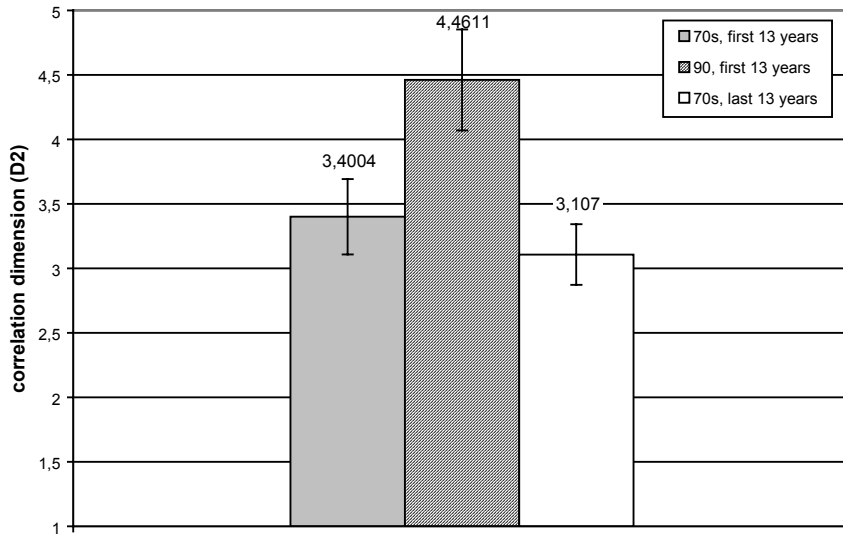
Table 3:   Correlation dimension (D2) of the three quasi-time series

period	70s cohort			90s cohort			T-Test (1-tailed)
	Mean D2	standard deviation	N	mean	standard deviation	N	
First 13 years	3.4004	0.2923	94	4.4611	0.3906	88	**
Last 13 years	3.1070	0.2360	100	last 13 years 70s vs. first 13 years 90s			**

    * p < 0.05   ** p < 0.01

5.   Significance for the field of OB – opportunities and limitations

The approaches introduced here are just a small fraction of the methods, tools and algorithms currently used and discussed in chaos research. The chosen example – the question about the increasing complexity of careers for different cohorts of professionals as expressed in the complexity hypothesis – illustrates quite nicely the opportunities, but also the limitations of the contributions that systems theories and related methods can make to OB. The propositions in this chapter about the potential contribution of the conceptual frameworks and the methods outlined above build on the previous considerations. Theorizing about organizations, conceptualizing complexity and quantitative measures of complexity as well as the application to careers bring up some points that, in our view, constitute opportunities for progress in OB.

First, the use of systems theories as conceptualized in this paper allows OB to widen its focus. While the concentration on individuals and their behaviour is more than welcome and has greatly contributed to our understanding of processes in organisations, it has to be supplemented by a broader focus: behaviour in organisations is not organisational behaviour. Organisational reality cannot sufficiently be explained through the aggregation of individual behaviour and related individual intentions. While social systems theory tries to conceptualise the emerging phenomena of the interrelation of behaviour of two or more individuals as a construct of its own kind and not merely as an addition to individual behaviour, thus overcoming an ultimately individualistic perspective, the systems theories presented in this paper take another route. They try to get the whole system into perspective and develop various constructs that refer to key characteristics of systems: self-organisation, phase transitions, the issue of thresholds and the resulting changes in systems' behaviour, bifurcation, the inclusion of the temporal dimension are just a few of them. In this way, the use of systems theories helps OB to consistently overcome a too individualistic perspective. This is not only an enlargement, but a new quality because it enables OB to deal with partly neglected aspects of OB: the behaviour of organisations, i.e., larger systems instead of just dealing with behaviour in organisations.

Second, the concepts and methods presented here explicitly include the dynamics of systems. Thus, the temporal dimension and a change perspective are explicitly integrated into theorising and methods of analysis. In the case of some concepts, this is the centre of their contribution. For OB, this is more than welcome. Many of the concepts used in OB are hardly able to cope with the dynamic quality of larger systems.

Third, the use of systems theories in OB strengthens the link between debates within OB and the broader scientific discussion in other disciplines. As systems theories cover a broad disciplinary background and are applied to a wide range of problems in different areas, working with such concepts can greatly enhance our understanding of the reality OB is dealing with: behaviour in and of organisations. Since a great number of people with a great variety of scientific background work with these concepts and try to develop them further, a lot of impulses can be gained from these discussions that help further development of understanding OB. At the same time, the contributions from those different scientific perspectives help to avoid or at least reduce blind spots that inevitably develop within the dialogue of a small scientific discipline.

Fourth, systems theories and related methods as described here avoid major pitfalls of the earlier usage of these concepts in OB which has been largely metaphorical. In terms of gaining theoretical insight into phenomena this is hardly a problem since even – or, as some may argue, especially – a metaphorical use of theoretical concepts can contribute to new insight. At the empirical level, however, the situation is different. At least within an objective, "quantitative" paradigm of epistemology and methodology, the clear conceptualisation of theoretical constructs and its formalised operationalisation for empirical research is crucial. For the systems theories used in this paper this goes without saying. Largely rooted in natural sciences, mathematics and physics, they come from a tradition where operationalisation is a clear "must". In addition, mathematical formalisation is also widespread in these approaches. For the ap-

plication in OB, this has the advantage of avoiding a common trap: leaving "soft" phenomena "soft" in the sense of fuzzy in empirical terms, i.e., not being able to operationalise and/or formalise core constructs and assumptions within parts of OB. We know that acknowledging vagueness because the phenomenon or the knowledge that can be acquired about it in itself is vague does no mean being vague. Hence, we do not propose greater exactness than the phenomenon allows (in line with Aristotle's famous dictum, see Jonas 1974: 127). However, we are convinced that for some of the "soft" issues that OB deals with, more substantial conceptualizations and operationalisations can be found than are used today. Of course, some developments in personnel economics serve as a warning example not to overstretch it.

Fifth, introducing theoretical concepts and analytical methods that are able to describe and quantify OB phenomena in a precise and methodically sound way do not only help to gain OB more reputation in a scientific world largely fascinated by mathematical clarity. It also has an at least partly healthy effect for the self-discipline of research efforts in OB. Well-sounding concepts alone are not sufficient if they cannot be used in empirical research – at least for some types of knowledge creation.

Sixth, the possibility to formalise key constructs and assumptions generates some connectivity to other dominant paradigms in the more management related parts of OB. For example, concepts within the micro-economic paradigm usually have a high degree of formalisation making the relationship between the different variables very clear. The dialogue between such an approach and less formalised ways of doing empirical research is sometimes made difficult because of the different underlying assumptions about "good science". While in the conceptual realm these differences sustain when using systems theories as outlined in this paper, the methods used and the use of stringent mathematical formalisation which is not metaphorical can help to build bridges for mutual understanding.

To be sure, there are a number of limitations, too. From a theoretical perspective, the high degree of abstraction limits the depth of analysis. Likewise, some critics would argue that organisations as social systems are a quality of their own. The elements of such systems – in this view individuals – have a greater freedom of choice compared to atoms or other types of non-living systems. Therefore, the unchanged application of such theoretical views might encounter difficulties.

From the perspective of methods, two main obstacles occur. First, the data that can be collected within an OB setting will in many cases not meet the standards in terms of numbers and time-span covered that are required to successfully apply the methods described in this paper. For example, we did not attempt to demonstrate here that the observed career paths are chaotic processes in a mathematical sense, as this would have to be done via the calculation of Lyapunov exponents for which the available data are unsuitable. Second, the methods employed are far less widely used than "standard" statistical procedures. This is also reflected in a lack of computer software that can perform this sort of calculations.

6. Concluding remark

Trying to be innovative in science is always linked with risks: what is innovative in one field may be yesterday's wisdom in another, the standards for evaluating the degree of

innovation vary between different observers, or the innovation ultimately does not lead to new insight. Nevertheless, as Kurt Lewin once wisely pointed out, it is often necessary to break established methodological taboos which ban methods or concepts as "unscientific" or "illogical" that later in scientific history have turned out to form the basis for a step forward (Lewin 1949, cit.op. Marrow 1977: 23). We do not assume that our paper will be worthy of this dictum – but at least it is encouraging to try.

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