PROJECT DESCRIPTION
FOR PROPOSALS TO COMPLEXITY SCIENCE

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RTI initiative:	Complexity Science
Full title of project:	Complexity as an Early Warning Signal for Phase Transitions in Psychology and Economics
Short title of project:	Complexity & Change
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Project partner(s):	Name(s) of institutions
Project duration:	
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Project goals

Radical, disruptive change processes are major challenges for human beings (e.g. the onset of a psychological crisis) as well as for economic systems (e.g. the onset of a financial crisis). Based on Synergetics – one of the most profound complexity theories today – the onset of a radical change in complex systems can be predicted beforehand by so-called "early warning signals", which can be empirically observed by means of a sudden significant rise in complexity.

The goal of this project is to establish three working groups in Austria in order to test and further develop complexity measurements (working group A – Methods) which are able to predict radical change in psychological systems (working group B – Psychology) as well as in economic systems (working group C – Economics). Promising first results from our international and interdisciplinary network on all three working group issues are an excellent starting point for future research on new methods for coarse-grained and small data sets, as well as the understanding of psychological and economic change.

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KURZFASSUNG

Anfang 2019 findet sich die Behauptung, dass wir es in verschiedenen Lebensbereichen mit einer zunehmenden Komplexität zu tun haben über 5 Millionen Mal im Internet (Google-Suche nach der wortexakten Phrase „increasingly complex“). Dies mag einer der Gründe dafür sein, dass das Interesse an den *Complexity Sciences* in den letzten Jahren stetig gestiegen ist. Insbesondere plötzlich auftretende radikale Veränderungen, wie ein Zusammenbruch von Aktienmärkten oder plötzliche suizidale Krisen werden als komplexes Geschehen erlebt. Die damit verbundene Verunsicherung führt zu ähnlichen Fragestellungen in der Ökonomie und der Psychologie: wie kann das Auftreten komplexer, dramatischer Veränderungen verstanden werden?

Trotz der zunehmenden Bedeutung des Komplexitätsbegriffes bleibt eine Definition – auch in wissenschaftlichen Aufsätzen – häufig nebulös oder wird gar nicht angeboten. Einige Autorinnen oder Autoren scheinen sich nicht einmal der Tatsache bewusst zu sein, dass „Komplexität“ der zentrale Gegenstand sogenannter Komplexitätstheorien ist. Basierend auf diesen Theorien kann Komplexität klar definiert, empirisch gemessen und als Indikator für die Stabilität bzw. Instabilität eines Systemverhaltens verwendet werden. Während Komplexität in der Komplexitätsforschung als prinzipiell nicht vorhersagbares Systemverhalten definiert wird, kann ein plötzlicher signifikanter Anstieg der Komplexität ein präziser Indikator sein für eine drastische, radikale Änderung des Systemverhaltens in der nahen Zukunft. Solche radikalen Veränderungsprozesse stellen große Herausforderungen z.B. für Wirtschaftssysteme (z. B. das Einsetzen einer Finanzkrise) sowie für den Menschen dar (z. B. das Einsetzen einer psychischen Krise). Basierend auf der von Hermann Haken begründeten Synergetik (Haken, 1969, 1990b, Haken & Schiepek, 2010) – eine der bedeutendsten Komplexitätstheorien der letzten Jahre – kann die zentrale Hypothese unseres Forschungsantrages wie folgt formuliert werden:

> Das Einsetzen einer radikalen Veränderung in komplexen Systemen kann durch sogenannte "Frühwarnsignale" vorhergesagt werden. Ein solches „Frühwarnsignal“ ist der plötzliche signifikante Anstieg der Komplexität in einem System.

Ziel des Projekts ist die Einrichtung von drei international besetzten Arbeitsgruppen in Österreich, um Methoden der Komplexitätsmessungen (Arbeitsgruppe A – Methoden) zu prüfen und weiterzuentwickeln, die radikale Veränderungen in psychologischen Systemen (Arbeitsgruppe B – Psychologie) sowie in Wirtschaftssystemen (Arbeitsgruppe C – Wirtschaft) vorhersagen können. Wenn es gelingt, das Auftreten dramatischer Veränderungsprozesse wie einer psychologischen Krise oder einer Wirtschaftskrise durch „Frühwarnsignale“ vorherzusagen, kann dies für Wirtschaft, Politik, Gesellschaft und den Einzelnen von großem Nutzen sein. Zudem kann durch die Zusammenarbeit von Methodologie, Psychologie und Ökonomie an dem gemeinsamen Thema ein Gewinn für alle drei Fachdisziplinen erwartet werden.

Obwohl unser international aufgestelltes Netzwerk in den letzten zehn Jahren recht erfolgreich war, stehen wir nun an einem Scheidepunkt, an dem nur eine Förderung es ermöglichen kann die angedeuteten wissenschaftlichen Ziele auch zu erreichen und die Forschungsposition Österreichs im Bereich der komplexitätswissenschaftlichen Zugängen zur Psychologie und Wirtschaftswissenschaft zu sichern und auszubauen. Aktuell gibt es in unserem Netzwerk das dafür notwendige Wissen sowie junge interessierte Wissenschafterinnen und Wissenschafter. Wir verfügen über Methoden, Software und Daten. Was wir jedoch brauchen, ist ein österreichisches Forschungszentrum, um diese verstreuten Potentiale zu bündeln. Wie wir in unserem Antrag zeigen, ist eine solche Bündelung möglich und eine fruchtbare Anstrengung.

ABSTRACT

Searching the internet, the term “complexity” seems to be at the heart of an uncountable mass of pages preaching the advent of an increasingly complex world: in January 2019 the phrase “increasingly complex” can be found more than 5 million times on the internet (google search of the exact phrase). This may be one of the reasons, why interest in complexity research and science has risen steadily in recent years. In particular, sudden radical changes, such as the collapse of stock markets or psychiatric, suicidal crises, are experienced as complex events, which are creating a fundamental uncertainty and are therefore inducing similar questions in economics and psychology: how can the emergence of complex crisis-like changes be understood?

However, the term “complexity” is not well defined in most of the popular pages, media, and even scientific papers (Horgan, 1995). Some of the authors do not even seem to be aware of the fact that complexity is the subject of the so-called complexity theories. Based on these theories, complexity can be defined, measured and can be used as an indicator for the stability versus instability of a system’s current state.

Therefore, while complexity itself is defined as being unpredictable, a sudden significant rise in complexity can be an accurate predictor of a dramatic, radical change of the system’s behaviour in the near future. Such radical, disruptive change processes are major challenges for economic systems (e.g. the onset of a financial crises) as well as for human beings (e.g. the onset of a psychological crises).

Based on Synergetics (Haken, 1969, 1990b, Haken & Schiepek, 2010) – one of the most profound complexity theories today – the main hypothesis of our proposal can be formulated as follows:

> The onset of a radical change in complex systems can be predicted beforehand by so-called “early warning signals”, which can be empirically observed by means of a sudden significant rise in complexity.

The goal of this project is to establish three working groups in Austria in order to test and further develop complexity measurements (working group A – Methods) which are able to predict radical change in psychological systems (working group B – Psychology) as well as in economic systems (working group C – Economics). The possibility to predict and understand the occurrence of disruptive change processes like psychological crises or economic crises by “early warning signals” could be of great use to economy, politics, society, and the individual. Additionally, the collaboration of methodology, psychology and economics on the subject of sudden change will be beneficial for all three disciplines.

Despite the fact that our international network has been quite successful in the last decade, funding of our proposal will be a significant push forward in order to secure and extend the research position of Austria to become a lead player for the application of complexity sciences to psychology and economics. Today we have the knowledge, methods, software, data and freshly graduated students as well as doctoral students and post-docs in our international network. However, what we need is a “home institution” to bundle these scattered potentials in Austria. As we show in our proposal, such an endeavour is possible and will be a fruitful effort.

1 QUALITY OF THE PROJECT

1.1 State of the art – current level of technology/knowledge

1.1.1 Introduction

Searching the internet, the term "complexity" seems to be at the heart of an uncountable mass of pages preaching the advent of an increasingly complex world (Strunk, 2019, Strunk & Schiepek, 2014). In January 2019 the phrase "increasingly complex" can be found nearly 5 million times on the internet (google search of the exact phrase). This may be the reason why interest in complexity research and science has risen steadily in recent years. The term "complexity" however, is not well defined in most of the popular pages, media, and even scientific papers (Horgan, 1995). Some of the authors do not even seem to be aware of the fact that complexity is the subject of the so-called complexity theories (this is addressed by a research-program on complexity at the FH Campus Vienna[1]). Based on those theories, complexity can be defined, measured and can be used as an indicator for the stability vs. instability of a system's current state (Strunk, 2019). Therefore, while complexity itself is defined as being unpredictable, a sudden significant rise in complexity can be an accurate predictor of a dramatic, radical change of the systems behaviour in the near future (Haken, 1969, 1977, 1990b). Based on the onset of so-called critical fluctuations, which are highly complex episodes of a system dynamic (Haken, 1990b), we are able to predict a suicidal crisis a day before the crisis becomes obvious (Fartacek, 2016). Schiepek et al. (2001, also: Strunk & Schiepek, 2006, 2014) were able to show that the occurrence of such highly complex episodes are also predictive for the outcome of psychotherapy. And in economics, too, there are findings from our network (e.g. Strunk, 2019) and others (Lo, 2005) that relate dramatic changes in complexity to relevant market events. But not only psychological or economic systems are indicating radical change processes beforehand through an increase in complexity. Radical change processes can be interpreted as phase transitions and such phase transitions are a central issue of one of the most influential complexity theories, called Synergetics (e.g. Bandt & Pompe, 2002, Collet & Eckmann, 1980, Haken, 1969, 1977, 1990b). Synergetics shows that phase transitions are generally "introduced" by critical fluctuations. This is a general phenomenon that has been observed in various systems of very different disciplines including natural sciences, live sciences, and social sciences (e.g. Haken & Schiepek, 2006). Accordingly, critical fluctuations can be used as early warning signals for disruptive change processes in general. Promising first results come from our internationally working group for psychology / psychotherapy and economic systems. However, there are still major research gaps:

(1) **Research gap – methods:** While there are complexity measurements available for extremely long, high quality, noise-free, stationary time series, we lack methods for real world data sets, which are non-stationary, noisy, short termed and coarse-grained (research from our working group: Schiepek & Strunk, 2010, Strunk, 2019).
(2) **Research gap – predictive value of critical fluctuations for psychological systems:** While there are promising results from our working group for the prediction of psychotherapeutic progress, we need much more testing with larger samples, different complexity measure-

[1] [German site]: https://www.fh-campuswien.ac.at/forschungsfelder/public/forschungsfeld-secure-societies.html

ments and regarding different outcomes (e.g. progress, failures, sudden gains and losses, occurrence of a psychological crisis, suicidal crisis, research from our working group: Fartacek, 2016, Plöderl & Fartacek, 2018, Olthof et al., 2018). What we need is a tabulation of sensitivity and specificity for different complexity measurements as predictors for different outcomes. Moreover, learning in general can be interpreted as a qualitative change process, which is accompanied by critical fluctuations (e.g. research from our working group: Strunk & Schiepek, 2006). This can be a fruitful view on individual learning processes (research from our working group: Sender, 2017), organisational learning (research from our working group: Liening et al., 2013) or decision making processes (research from our working group: Rose, 2012, Strunk et al., 2015b).

(3) **Research gap – nonstationary complexity measurements in economic systems:** In recent years support for the most famous hypothesis of financial literature, the efficient market hypothesis (Fama, 1970, 1991, 1998) has become highly controversial (Malkiel, 2003, Shiller, 2003). While the efficient market hypothesis predicts a development of a market to efficiency, there is a growing number of literature showing that markets are sometimes more and other times less efficient (Lo, 2004, 2005). Therefore, we see linear and nonlinear dependencies in complexity measurements rising and falling (Lo, 2004; research from our working group: Feigl, 2011, Glinsner, 2019, Griessmair, 2005, Peša, 2019, Strunk, 2019, Wagner, 2019). First promising results from our working group show "early warning signals" in complexity measurements before critical events like the onset of a financial crisis (research from our working group: Griessmair, 2005, Strunk, 2019), or the publication of quarterly financial figures of stock market companies (research from our working group: Wagner, 2019). We need a better understanding of such "early warning signals" and deeper insights into how markets are reacting to crises and external shocks with a varying complexity.

In summary, the main goal of our project is to proof the usefulness of different complexity measurements (working group A – Methods) for the prediction of change processes (phase transitions) in psychology (working group B), and in economic systems (working group C). Additionally, the collaboration of methodology, psychology and economics on the subject of sudden changes will be beneficial for all three disciplines. Economic research like behavioural finance for example has already begun to study psychological influences on markets. The human experience of dramatic change can be impelling for further unfavourable market developments. Similar processes could play a role in purely psychological crises as well. In addition, time series analysis has a long tradition in economics, which can be beneficial for Psychology. Particularly event studies, known from economics, can be used as templates for analysing psychological events. Furthermore, both disciplines are in need of methods able to handle the limited and at times inaccurate data collected in the field.
In the following chapter 1.1.2 we will at first discuss general aspects of complexity, Synergetics and phase transitions as a common framework (discussed in Strunk, Schiffinger & Mayrhofer, 2007; Liening, Strunk & Mittelstädt, 2013). Later on, we illustrate the use of this framework with regard to complexity methods (1.1.3), psychology (1.1.4) and economics (1.1.5).

1.1.2 Complexity and Self-organising Processes

There is no one theory of complexity and therefore we need a rough definition of how we define the term and why we argue that a sudden rise in complexity is a predictor of a major change process. Our view on complexity is based on two research traditions. The first one is theoretical and therefore able to explain complexity (e.g. chaos theory, Synergetics). The second one is more pragmatically interested in methods able to identify complexity (e.g. fractal geometry) or randomness and order (e.g. algorithmic entropy), which are both not complex at all:

(1) **Complexity theories are able to explain complexity**: It can be shown that a fully deterministic system is able to show behaviour, which is not predictable in the long run (e.g. Lorenz, 1963). Moreover the behaviour is said to mimic randomness (Ramsey et al., 1990, p. 991, Liu et al., 1992, p. 26, Serletis & Gogas, 1997, p. 360, Chwee, 1998, p. 150), which is not technically correct but gives a good impression of what is meant. It was a big surprise for Henry Poincaré (1908), Edward N. Lorenz (1963), or Ruelle and Takens (1971) to have found a non-trivial, non-predictable process as a result of a well-defined purely deterministic equation system. The now well-known butterfly-effect (Lorenz, 1963) describes the mechanism of this form of complexity (a more detailed view gives the backer-transformation Nicolis & Prigogine, 1987, p. 271 ff., Schuster, 1989b, p. 107 f.). From this point of view complexity is seen as a non-predictable process, which looks random but is not random. This is because we can find the butterfly-effect even in equation-systems without any random term. Those systems are fully deterministic. However, they behave very different compared to linear equation systems. Linear equation systems, irrespective of how many variables are involved, are always fully predictable. Therefore, complexity is located in the tension field between trivial order (known from linear systems) and randomness (known from random systems), but is not identical with one or the other (research from our working group: Strunk, 2009b). Consequently, it is a quality of its own, showing both order and unpredictability simultaneously. Thus, complexity seems to be a paradox of contradicting principles. This can be considered as a major reason why it has taken considerable time to understand this phenomenon.

(2) **Methods of complexity research are able to identify complexity:** If a deterministic equation system is able to mimic randomness, the influence of determinism must be identifiable in time series data of such a deterministic but complex system. Methods of complexity research are based on the identification of ordered patterns (e.g. periodicity, recurring states, Guastello, 2000, Guastello et al., 1998, Morse & Hedlund, 1938, from our working group: Strunk, 2019, Strunk & Schiepek, 2002), randomness (e.g. iid Brock et al., 1996, Brock et al., 1987) or special markers of chaotic systems (e.g. butterfly effect, fractal geometry of strange attractors Rosenstein et al., 1993, Sato et al., 1987, Wolf et al., 1985 from our working group: Strunk, 2019). Interestingly some methods are much older as the complexity theory outlined above (e.g. Morse & Hedlund, 1938) or are formulated without connection to deterministic chaos. Algorithmic entropy (Zvonkin & Levin, 1970) for example defines order as an algorithm, which is able to (re-)produce a data set. If a data set is looking complex with the naked eye but a small and simple algorithm is able to (re-)produce it, the data set is best interpreted not as a result of a complex but of a simple system. So algorithmic complexity is not interested in complexity (e.g. its roots and causes), but in simple rules behind complex looking phenomena. If such a simple rule cannot be found the system may be either random or complex.

Complexity seen as a non-predictable non-random process is nowadays classified as a self-organised behavioural pattern and is called an attractor of the system (e.g. Strunk, 2019). Such a pattern is not arbitrary (like randomness) but something like a stable template with random-looking variations within the pattern of that template. Like no snowflake looks like the other, they are all build on the basis of the same rules and are looking similar enough to be identified as snowflakes (Mandelbrot, 1977). Therefore, self-organisation means the emergence of a stable pattern (attractor), regardless of its complexity. One of the most influential theories for the understanding of self-organising processes in complex systems is called Synergetics and 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 (Haken, 1970). 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 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 this pattern. Before self-organisation sets in, there is a "tournament" of possible behaviours (modes). At this stage, the elements' behaviour is of extreme complexity (or randomness), which is therefore a marker for the tournament process. Put in an oversimplified way, at this stage every element does what it likes to do. The technical term for this state, where all possible modes may happen with equal probability, is "symmetry".

As soon as self-organisation starts, a radical change called a "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. In other words, the symmetry between the possible modes is broken down, resulting in one dominating mode. 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). Self-organisation, which here means the development of an ordered mode (the 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 their 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.

An example from language (see Haken, 1979, p. 8) can illustrate various aspects that have been addressed above, especially the self-organised interplay of micro and macro level. 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. *This is one source of what we call the complexity of a complex system.*

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. *This is one source of what we call the orderedness of a complex system.*

As we have shown, self-organisation on the macro level of a system's behaviour means the formation of organised structures, i.e., of ordered patterns. While simple, easily predictable behaviour is characteristic for trivial systems, self-organisation in complex systems becomes manifest by highly complex yet ordered patterns. Therefore, the sequence of letters "this is a man" appears much more complex than the alphabetically sorted "original" sequence. The sequence of symbols which this proposal consists of is highly complex, and this is what makes this application 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 computer program. 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. As

seen above, the distinction between random, trivial and complex order is the core concept of an empirical complexity research (see Table 1 below).
Based on the framework of Synergetics – which was outlined above in a simplified way – we are able to draw some conclusions about the possibility for the prediction of a phase transition in the near future of a system. Synergetics shows that self-organisation in complex systems is comparable to the behaviour of simple well-known and well understood equilibrium systems, but the concept of homeostasis is widened and more powerful here. As in equilibrium, systems are able to preserve their preferred behavioural patterns even in the presence of small external or internal perturbations. This preferred behavioural pattern is called an order parameter or attractor; it is not limited to a trivial fixed-point behaviour, but can be of high complexity as in the case of strange attractors (Ruelle & Takens, 1971), which are typical for deterministic chaos. Therefore, one of the central methodological concepts in Synergetics is the stability analysis of the system's behaviour. In case of adhering to an attractor the system is able to compensate for external or internal perturbations. However, complex systems are able to develop different attractors, and alterations between them can be identified by the deceleration of stability and a growing influence of external and internal fluctuations. This stability analysis can be conducted either analytically, on the basis of mathematical models (Haken, 1977), or empirically, on the basis of time series data from a system under study (e.g. from our working group: Schiepek & Strunk, 2010) and can be used to visualise the stability of an attractor in a graph, which is called a potential landscape.
Within a potential landscape a stable attractor can be visualised as a ball in a valley (Klaus et al., 1927, p. 35, cf. Kim & Wang, 2007); see Figure 1. The ball is always seeking for the deepest spot of the valley; therefore, external or internal perturbations are usually not able to permanently remove it from the preferred deepest point. Or in other words: the system perseveres its preferred course of action against external or internal changes and fluctuations. Stability analysis in Synergetics makes it possible to determine the steepness and latitude of the valley empirically. In Synergetics, radical changes in behaviour are referred to as phase transitions and appear as changes in the stability of the self-organisation processes. Therefore, Synergetics would be in a position to observe, explain and, in many systems, also to predict behavioural changes.

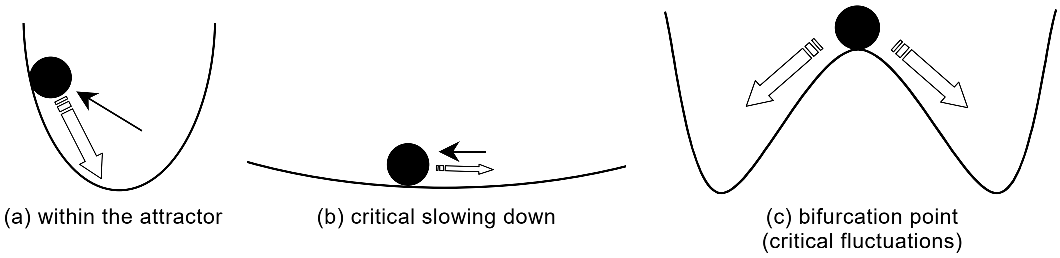

Figure 1: Consecutive Stages of a Phase Transition Represented as Potential Landscape. From Strunk and Schiepek (2006, p. 295).

The figure shows a special kind of a phase transition known as cusp-catastrophe in catastrophe theory and was already modelled for different real-world-systems (e.g. Bigelow, 1982, Gresov et al., 1993, Guastello, 1995, 2000). However, within our framework the concrete shape of the potential landscape is not the main concern. Independent of the actual type of transition our main focus is on the onset of critical fluctuations as a marker for a phase transition. Phase transitions occur far more rarely than simple corrections within the framework of an existing attractor (Haken & Wunderlin, 1991). Additionally, a system is normally trapped by an attractor and sticks to it, even if a more appropriate attractor is available. Therefore, Synergetics can demonstrate the so-called hysteresis effect (sticking to an attractor longer than adequate) in various systems. Hysteresis has been empirically illustrated within learning processes for instance in human hand movement (Haken et al., 1985, Kelso, 1990, 1995), problem-solving tasks (Haken & Stadler, 1990) or perception (Haken, 1997, an overview for Synergetics in psychology from our working group: Strunk & Schiepek, 2006). In case of a phase transition, the stability of the previous behavioural pattern decreases more and more (Haken, 1977, p. 105). External and internal perturbations are not being immediately corrected anymore; error correction within the attractor is slowing down. Stability analysis can empirically show this so-called "critical slowing down" (Haken, 1977, p. 110; Haken, 1990b, p. 9). At the same time, the relevance of internal and external fluctuations increases. The system is losing its previous stability and for a short moment of time becomes a "will-less puppet" in the "hands" of its environment. This loss in stability can be proven through the increase in complexity by employing methods from chaos and complexity research and is called "critical fluctuation" (Haken, 1990b, p. 9). For psychotherapeutic learning processes it could be shown that for clients such changes were accompanied by discomfort and resistance (from our working group: Strunk, 2004). Normally, systems do not let themselves be exposed to such openness and try to re-establish the self-organisation processes. As already seen above, Haken has proven for several systems, that this re-establishment is accompanied by a highly selective competition of different behavioural possibilities (modes) in search for a new attractor. So on the micro level the system starts "brain-storming", which comes in as a wild fluctuation storm, before the onset of feedback processes results in a growing stabilisation of an increasingly dominant mode (Haken, 1977). Therefore critical fluctuations are much more than just external perturbations, they are evidence for the systems "search" for a new stable state. Phase transitions are key features of many systems and were even well-known before the advent of Synergetics, bifurcation theory or catastrophe theory (see for examples Stadler & Kruse, 1990). However, the occurrence of phase transitions in systems far from the thermodynamically equilibrium is not trivially explained. All three named theories are interested in the understanding and empirical modelling of phase transitions, bifurcations or catastrophes. Therefore one will find Figure 1 in textbooks for all three theories. Nonetheless, they are based on different assumptions, mathematical models, and empirical approaches. Haken (1977, p. 133-145) for instance has introduced catastrophe theory from within the framework of Synergetics. He shows that the mathematical formalisation of a catastrophe is not in every case adequate for the modelling of systems far from equilibrium, but was able to show, that in a limited set of systems near a phase transition catastrophe models are sometimes equivalent to mathematical deductions derived from Synergetics (Haken, 1988a, 1988b). In contrast to other theories for the explanation of phase transitions like catastrophe theory (Thom, 1972) or bifurcation theory (Feigenbaum, 1978),

> Haken's work, from its very beginning, always includes an essential role for, and explicit treatment of, microscopically generated fluctuations. This is also where it deviates from Thom's … theory [Footnote 29: For a highly informed analysis of the main themes of Haken, Prigogine, and Thom, see Landauer, R. (1981) …]. Fluctuations, as we will see, turn out to be quite crucial, both conceptually and methodically, to our understanding of self-organisation … (Kelso, 1995, p. 42)

Additionally, the mathematical underpinnings of Synergetics are founded on a broader basis than e.g. catastrophe theory. So Synergetics make it possible to explain phase transitions in and out from deterministic chaos and to handle deterministic chaos as a genuine property of the nonlinear dynamic equations that Synergetics deals with (Haken, 1988a, p. 170). In the early 1970s there were a lot of discussions about which theory is more powerful and of more practical use for the understanding of phase transitions (e.g. Landauer, 1981). We do not need to continue this discussion here. Instead, we will focus on the main lesson from Synergetics: It is possible to monitor phase transitions on the basis of critical fluctuations (Haken et al., 1985, Kelso, 1990, 1995).

1.1.3 Methods for the Identification of Critical Fluctuations and Phase Transitions in Short Term and Coarse-grained Time Series (Working Group A – Methods)

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 (Table 1, next page). Most of these algorithms have been developed in the last 30 years, frequently based on older precursors (see for a comprehensive discussion on all relevant methods today, results from our working group: Griessmair et al., 2011, Liening et al., 2013, Schiepek & Strunk, 2010, Strunk, 2009a, 2012, 2013, 2019, Strunk et al., 2004, 2007). The fast majority of methods is only applicable to stationary data sets (right column from Table 1, next page). However, change processes are non-stationary by nature. Additionally, valid methods require fine-grained measurement on an interval scale, with a time series length above 500 up to many thousand data points. In psychology, management sciences, and even economics, those data-requirements are actually not in reach (discussed in detail in: Strunk, 2019). Moreover, in order to force empirical research in the field of complexity we need an easy to use software-framework, like modern spreadsheet programs or statistical software. Results from our research group for all named challenges are promising (e.g. Schiepek & Strunk, 2010, Strunk, 2019, GChaos Software: www.complexity-research.com):

(1) Monitoring of non-stationary processes by classical methods: Methods from fractal geometry and for the identification of a butterfly effect (see Table 1, next page) are the most reliable and valid measurements for complexity today. However, data-requirements and the stationarity assumption are hindering the use for monitoring change processes. Our working group successfully implemented the pointwise D2-algorithm for psychotherapy research (Kowalik et al., 1997, Schiepek et al., 2014, Schiepek et al., 2016a, Schiepek et al., 1997, Schiepek et al., 1995b, Strunk, 2004) as well as for economic time series (Glinsner, 2019, Griessmair, 2005, Peša, 2019, Strunk, 2019, Strunk et al., 2015b, Wagner, 2019). However, such adaptions of stationary methods for non-stationary data sets are a major challenge. Until recently, the calculation of a fractal dimension as well as a Lyapunov-exponent was only possible for researchers with great experience and practice and was therefore not in every case objective, and extremely time consuming. In case of a non-stationary process, hundreds or even thousands of consecutive Lyapunov-exponents are needed in order to monitor only one change process. Therefore, we have developed fast and automatically adjusting algorithms in order to enhance classical stationary methods (overview in: Strunk, 2019, from our working group). All newly developed non-stationary enhancements have been extensively tested for economic as well as for psychological change processes. However, classical methods (like fractal geometry, Lyapunov-exponents) still require an interval scale and a fine-grained resolution of measurement as well as a relative long time series (between 100 up to 500 samples).

Method	Main Focus	Meaning of High values	Dynamic	Phase Space	Level of measurement	Minimum Data	Stationarity
Time-Lag Autocorrelation (Tsonis & Elsner 1988, Schuster 1989b, Tsonis 1992)	First minimum of dependencies.	Order	Dynamic patterns are of importance.	No.	Interval	$N \geq 30$	Required.
Time-Lag Mutual Information (Fraser & Swinney 1986)						$N \geq 30$	
Time-Lag Generalised Correlation Integral (Grassberger & Procaccia 1983a, 1983b, Liebert & Schuster 1989)						$N \geq 200$	
Phase Space Reconstruction (Packard et al. 1980, Takens 1981)	It is the first step for further analysis and not itself a measurement for complexity.					$N \geq 5$	
Fractals							
Strange Attractors D2 (Ruelle & Takens 1971, Mandelbrot 1977, 1982, Grassberger & Procaccia 1983a, 1983b, Mandelbrot 1987)	Fractal Dimension, degrees of freedom.	Complexity. Random processes are ruled out.	Geometric structure of phase space reconstruction but no dynamic aspect is analysed.	Yes.	Interval, with fine grained continuous scaling.	$N \geq$ 200-1,000 $N \geq 10^{\frac{D2}{2}}$	Yes.
PD2 (Skinner 1992, Kowalik & Elbert 1994, Skinner et al. 1994)	Pointwise (for each sampling point) calculated fractal dimension, degree of freedom.		Geometric structure of phase space reconstruction but no dynamic aspect is analysed. However geometric structure is assessed pointwise for each sampling point.			$N \geq$ 200-1,000 ($N \geq 10^{D2/2}$) Pointwise calculation requires 75% valid points in order to be interpreted.	No. Problems with non-stationarity of embedding are usually not discussed in literature.
PD2 with Bundled Focus Points (Strunk 2004)							
Butterfly Effect							
Largest Lyapunov-Exponent Wolf-Algorithm (Wolf et al. 1985)	Magnitude of butterfly effect.	Chaos, central concept of complexity.	Characterisations of dynamic processes are at the focus.	Yes. Also degrees of freedom are necessary in order to use a correct phase space reconstruction	Interval.	Minimum: $N \geq$ 2,000-5,000 or 10^m	Yes.
Largest Lyapunov-Exponent Rosenstein-Algorithm (Rosenstein et al. 1993)						$N \geq$ 100-500 10^D may be enough.	
Largest Lyapunov-Exponent Kantz-Algorithm (Kantz 1994)							
Local Largest Lyapunov-Exponent Wolf-, Rosenstein-, or Kantz-Algorithm	Changes of the magnitude of butterfly effect in time.		Dynamic properties are the main focus of the Lyapunov-Exponent. Additionally, changes over time are monitored.			Window Length: $N \geq$ 100-500 10^D may be enough.	No, within a moving window stationarity is assumed.
Entropy							
K2-Entropie (Grassberger & Procaccia 1983a, 1983b, Frank et al. 1993)	Entropy as a global measurement for the butterfly effect.	Complexity. Random processes are ruled out.	Geometric structure of phase space reconstruction but no dynamic aspect is analysed.	Yes.	Interval, with fine grained continuous scaling.	$N \geq$ 200-1,000 $N \geq 10^{\frac{D2}{2}}$	Yes.
PK2 (Kowalik & Elbert 1994, Skinner et al. 1994)	Pointwise (for each sampling point) calculated entropy.		Geometric structure of phase space reconstruction but no dynamic aspect is analysed. However geometric structure is assessed pointwise for each sampling point.			$N \geq$ 200-1.000 $N \geq 10^{\frac{D2}{2}}$ Pointwise calculation requires 75% valid points in order to be interpreted.	No. Problems with non-stationarity of embedding are usually not discussed in literature.
Recurring States							
Recurrence Plot (Zbilut & Webber Jr. 1992, Webber Jr. & Zbilut 1994, Marwan 2003, 2006)	Consecutive recurring states are identified and its length or position is counted.	Recurring ordered pattern are identified.	Dynamic properties are the main focus of the method.	Yes.	Interval.	$N \geq 32$	The plot itself is used in order to give an impression of non-stationarity. However quantitative measures of recurrence plots are assuming stationarity.
Low Level of measurement							
Information Definition (Shannon-Entropy) (Shannon 1948)	Deviation from equally distributed frequency distribution (which is maximum complexity).	Complexity with known upper limit for randomness.	No dynamic aspect is analysed.	No.	Nominal. Higher levels are handled by discretisation.	$N \geq$ 5-30	Yes. However, moving windows are easy to implement for those methods for small data sizes.
Symbolic Dynamics (Shannon-Entropy for Words) (Shannon 1948, Collet & Eckmann 1980)			Within words dynamic aspects are considered.	No, but possible.		$N \sim 10^{2m}$, with 10 categories.	
Permutatio Entropy, Group of GEntropies (Bandt & Pompe 2002, Strunk, 2019)					Ordinal.	$N \geq$ 20-400	
Grammar Complexity (Ebeling & Jiménez-Montano 1980, Jiménez-Montano 1984)	Ability to compress a dataset.	A high compression indicates order.	Dynamic properties are the main focus of the method.	No.	Nominal. Higher levels are handled by discretisation.	$N \geq$ 10-30	
Dynamic Complexity (Schiepek & Strunk 2010)	How scattered are the values within the range of a given rating scale.	High values are indicating complexity.	Dynamic properties indicating scattered volatility are recognized.	No.	Interval or Ordinal.	$N \geq 7$	

Table 1: Methods for the identification and quantification of complexity, randomness or order. All methods are implemented in GChaos and are used for psychological as well as for economic time series (Table based on Strunk, 2019).

(2) **Newly developed methods for coarse-grained and small data sets:** Methods for small data sets with little quality of measurement level are much promising recent developments of several working groups worldwide. Our working group as well has contributed to these promising advances in complexity research (e.g. Schiepek & Strunk, 2010, Strunk, 2019). However, such methods give a rough quantification of scattered volatility and are therefore no valid quantification of a deterministic chaotic process. Nevertheless, they fit much more to data levels available in psychology and economics. As this branch of technology development in complexity research is just at its beginning, much more work is to do. Especially sensitivity and specificity for the identification of phase transitions in simulated and real-world data sets are unknown for most of the newly developed algorithms.

(3) **Software development:** Today, there is only one extensively tested and easy to use software for complexity research available. It has been developed and tested since 1992 by our working group (GChaos, www.complexity-research.com, Strunk, 2019) and can be downloaded for free from complexity-research.com. In contrast to other packages on complexity measurements, non-stationarity is the main focus here. However, much more optimisation is needed: of algorithms as well as of usability and support for ideal parameter settings in order to reach high sensitivity and specificity for the prediction of change processes.

Summarising, the goals of Working Group A – Methods are:

- The development of new methods, like the Shannon based GEntropies (Strunk, 2019), a Cross Lyapunov Exponent (Strunk, 2015, Strunk et al., 2015a, Strunk & Schiepek, 2014), methods for rating scales like the Dynamic Complexity (Schiepek & Strunk, 2010), methods for the simplification of classical algorithms (Strunk, 2019), etc.
- The extensive testing of sensitivity and specificity for the prediction of change processes of (1) classical methods as well as of (2) newly developed methods for (a) simulated data and real world data from (b) psychological measurements, and (c) economic time series.
- Improving the GChaos Software (e.g. memory usage, processing time, open architecture, use of new C++ features, handling of more data-file-formats etc.).
- The theoretical models and measurement models of psychology and economics require appropriate methods that must be developed in cooperation with methodologists. Therefore, profound support and cooperation with the other working groups is one goal of Working Group A.
- Development of applications (“early warning systems”) for industry and health care providers, in collaboration with the other working groups.

1.1.4 Critical fluctuations and Phase Transitions in Psychology (Working Group B – Psychology)

The nature of many psychological processes can best be described as “organised complexity”. Behavioral, emotional, cognitive, perceptive, etc. processes are not purely ordered like simple mechanical clockwork automates (see the discussion on the human as an automat metaphor in Strunk & Schiepek, 2006). On the contrary, psychological processes are highly complex (in the above defined sense) and therefore not predictable in the long run. However, they are patterned, and organised and therefore not purely random as well. Therefore, the advent of theories of nonlinear dynamic systems became the basis for the understanding of such pro-

cesses in psychology[2]. Based on nonlinear dynamic systems theories, research from our working group proposed a so-called "Systemic Psychology" (Strunk & Schiepek, 2006), and summarised empirical research for different psychological disciplines as well as for underlying biological processes (e.g. motoric control, cardio-vascular system, neuro physiology). Components of a "Systemic Psychology" are patterns of organised complexity. This view is a logical step on a ladder starting with the classical stimulus-response-model (S-R, see Rescorla, 1988, Skinner, 1935, Strunk & Schiepek, 2006, Watson & Rayner, 1920). The S-R-model provides a simple component as a core element of which psychological processes are composed. As such, every psychological process was seen as a composition of simple S-R-elements. A cybernetic view was introduced as a more appropriate view on psychological processes by Miller, Galanter and Pribram in the 1960s (Miller et al., 1960). The core element of a psychological process is now a feedback-control-system, the cybernetic TOTE-process. However, as seen above a feedback-control-system is limited to equilibrium, which is called a fix-point process. The concept of an attractor in nonlinear system theories is much more flexible but has the same advantages as the feedback-control-system for the explanation of self-organised stability in complex systems. So the attractor is introduced as the core element of psychological systems in the Systemic Psychology by Strunk and Schiepek (2006, however the fruitfulness of Synergetics or other such theories for psychology was also discussed earlier by others, e.g. Basar et al., 1983, Haken, 1990a, 1992, Haken et al., 1985, Haken & Stadler, 1990, Kelso, 1990, Kriz, 1990, Schöner et al., 1986, Stadler & Kruse, 1990, Tschacher & Scheier, 1995, Tschacher et al., 1998, Tschacher et al., 1992).
An attractor is organised and resistant to external and internal fluctuations. Its behavioural pattern is not limited to homeostasis but widened for all kinds of behavioural patterns a nonlinear system is capable of including deterministic chaos. Additionally, particularly Synergetics can explain how an attractor emerges by self-organisation from a competition of numerous degrees of freedom (like a brainstorming-process). Therefore, change in the stability of an attractor is the main focus of Synergetics, and – as seen above – such a change can be identified by early warning signals like the onset of critical fluctuations and the so-called critical slowing down (see above, Figure 1). In summary, a phase transition (which is a change of attractor) is a potent model (not only limited to, but also) for a qualitative learning process and therefore at the heart of what psychological research deals with, namely the change of behavioural, emotional, cognitive or perceptive patterns.
However, while the theoretical concept drafted here is extremely promising, empirical evidence is scarce. The most advanced branch on this regard is the field of psychotherapy process research. Starting in the early 1990s research from our working group shows evidence for the named change processes in psychotherapy on the basis of two single case studies on the micro-level of psychotherapeutic interaction (Kowalik et al., 1997, Schiepek et al., 2014, Schiepek et al., 2016a, Schiepek et al., 1997, Schiepek et al., 1995c, Schiepek & Strunk, 1994b, Schiepek et al., 1995b, 1995a, Strunk, 2004, Strunk & Schiepek, 2002, Walter et al., 2010) as well as for daily data from N=941 psychotherapeutic patients (e.g. Schiepek et al., 2016b, Schiepek et al., 2014, Strunk et al., 2014). Results show that therapist-client interactions fulfil the prerequisites of deterministic chaos: irregularity of the process, phase transitions, restricted prediction horizon, and still some global order of the dynamic process. These results

[2] It must be noted here that some areas of classical academic psychology still do not agree with the change of perspectives towards a "systemic psychology".

suggest that the client-therapist-relation and psychotherapeutic change are indeed self-organising processes that emerge from moment-to-moment transactions between therapist and client (best overview is given in: Strunk, 2004). Phase transitions at the micro-level of a moment-to-moment client-therapist-interaction are accompanied by critical fluctuations (variance of the local butterfly effect) and emotionally by resistance or engagement (Strunk, 2004). Data from daily patient ratings show similar results for a larger sample but more macro-level time series (e.g. Schiepek et al., 2016b). Particularly the occurrence of critical fluctuations seems to be a prognostic factor for therapy outcome (e.g. Haken & Schiepek, 2010) or the occurrence of sudden gains or losses (Olthof et al., 2018). Additionally, first results are showing that a suicidal crisis can be predicted by critical fluctuations the day before the crisis sets on (Fartacek, 2016, Plöderl & Fartacek, 2018). With regard to deterministic chaos we have found strong evidence for an exponential divergence of the course of disease even between patients with the same diagnosis (Strunk, 2015, Strunk et al., 2015a, Strunk & Schiepek, 2014).
Simply spoken, for psychotherapy a problematic behavioural pattern can be interpreted as an attractor and psychotherapy itself as a process in which phase transitions are stimulated. Such processes are also an issue in learning psychology and didactic. Research from our working group by Sender (2017) was concerned with the occurrence of critical fluctuations as a marker of what is called the aha-effect (Bühler, 1930) in psychology and the liminal space in newer didactic research (Meyer & Land, 2005). He used learning diaries as well as heart rate complexity measurements in order to show critical fluctuations in learning processes and was able to show a significant relevance of such critical fluctuations for the outcome of a learning process. The same was found for processes of organisational learning (e.g. in the sense of Argyris & Schön, 1978, Argyris & Schön, 1996) by our working group (Liening et al., 2013, Mittelstädt et al., 2011) or economic decision making processes (from our working group: Rose, 2012, Strunk, 2019, Strunk et al., 2015b).
Summarising the change from stability through instability (critical fluctuations) to a new stability can be seen as a core element of psychological processes (e.g. learning, psychotherapy, stability in perceptual gestalt processes or cognition etc.) and was a theme also before the advent of the theories of nonlinear dynamical systems (e.g. Lewin, 1935, 1947, 1951, or in developmental psychology Piaget, 1953, Piaget, 1969/1936, 1969/1945, Piaget & Inhelder, 1969, or organisational learning Argyris & Schön, 1978, Argyris & Schön, 1996). Based on previous work from our working group we are able to build new research on a large dataset, which already exists and is still growing. For psychotherapeutic processes we have a collection of more than 900 cases from different sources (clinics, settings, diagnoses, therapists, etc.). However, we have just started with complexity analysis as a tool to forecast relevant change processes in psychology and organisational learning. Therefore, the goals of Working Group B – Psychology are:

- Further development of theoretical models to examine processes of change in psychology.
- Development of laboratory studies and real world studies on such change processes.
- Investigation of these specific psychological issues with methodology of complexity research in collaboration with the other working groups.

- The extensive testing of sensitivity and specificity of different complexity measurements for the prediction of relevant change processes in psychology and organisational learning.
- Empirical and theory-based identification of such early warning signals able to predict change processes with dramatic consequences (e.g. suicidal crises or crises in organisations).
- Development and improvement of methods for time series data gathering in psychology and organisational learning.
- Establishment of an open database for time series data in psychology and organisational learning.
- Cooperation with the other working groups in order to reach a deeper understanding of phase transitions in general and methods to predict such dramatic change processes.
- Development of "early warning systems" as applications for real world scenarios.

1.1.5 Critical Fluctuations and Phase Transitions in Economy (Working Group C – Economics)

In recent years support for the most famous hypothesis of financial literature, the efficient market hypothesis (Fama, 1970, 1991, 1998) has become highly controversial (Malkiel, 2003, Shiller, 2003). While the efficient market hypothesis predicts a development of a market to efficiency, there is a growing number of literature showing that markets are sometimes more and other times less efficient (Lo, 2004, 2005). Therefore, we see linear and nonlinear dependencies in complexity measurements rising and falling (Lo, 2004; research from our working group: Feigl, 2011, Glinsner, 2019, Griessmair, 2005, Peša, 2019, Strunk, 2019, Wagner, 2019). First promising results from our working group show "early warning signals" in complexity measurements before critical events like the onset of a financial crisis (research from our working group: Griessmair, 2005, Strunk, 2019), or before the publication of quarterly financial figures of stock market companies (research from our working group: Wagner, 2019). We need a better understanding of such "early warning signals" and deeper insights into how markets are reacting to crises and external shocks by exhibiting variations in complexity which are compatible to both the discussion on market efficiency as well as on critical fluctuations as marker for phase transitions.
Strunk (2012, 2019) summarises all publications on chaos and nonlinearity in economic time series (e.g. stock market data, exchange rates, etc.) published between 1988 and 2011. A total of 92 articles with 682 economic time series were summarised showing that nonlinear dependencies are regularly found. 83.5% of all time series analysed show strong evidence for nonlinear dependencies. Additionally, a positive Lyapunov-Exponent (butterfly effect) was found in 52% of time series analysed. Thus, results are mixed and it seems that some markets are showing sometimes nonlinear dependencies and even deterministic chaos, while from time to time the same markets or others are totally in line with market efficiency. So markets are not per-se efficient or chaotic, they change depending on inner or exogenous influences. Such influences may be interpreted as control parameters in the sense of Synergetics (see above).
However, the fast majority of research on economic time series (and also on psychological time series) is based on a stationary assumption (see above) which is seldom tested (see

Hamill et al., 2000, Hsieh, 1991, Kohers et al., 1997, McKenzie, 2001). Most used methods are the D2 (Grassberger & Procaccia, 1983b, 1983a), K2 (Grassberger & Procaccia, 1983c, 1983a), Lyapunov-Exponents (Wolf et al., 1985), and the BDS-Test (Brock et al., 1996, Brock et al., 1987). Moreover non-stationary analysis is missing with only a few exceptions (e.g. Czamanski et al., 2007, Lo, 2004, 2005). Czamanski et al. (2007) showed for the Alberta energy market episodes of linear and nonlinear dependencies:

> If we can learn how to detect when the energy market series become nonlinear then we can use linear methods for making short term forecasting during the linear regimes. There is no known method for forecasting nonlinear processes with non-zero bicorrelations and cross-bicorrelations. Forecasting of such nonlinear processes is an important and difficult mathematical and statistical problem that should attract more attention than it has received in the time series field. (Czamanski et al., 2007, p. 103)

It is interesting that probably the first analysis with the non-stationary PD2 was done within a master thesis by our working group in 2005 (Griessmair, 2005). Since these early studies we have replicated such analyses with different data-sets and different methods. Results show that complexity is varying in time and is high near a dramatic market relevant event (research from our working group: Feigl, 2011, Glinsner, 2019, Griessmair, 2005, Peša, 2019, Strunk, 2019, Wagner, 2019). It was Andrew Lo's (Lo, 2004, 2005) adaptive market hypothesis (AMH) which enforces a theory based discussion of non-stationary dependencies and varying complexity in markets. Argumentation of AMH is very similar to the view Synergetics offers on self-organising processes. Markets are under pressure all the time in order to react to new and unforeseen developments. Such external and internal demands are causing inefficiencies (measurable by linear and nonlinear dependencies) as long as the market has adapted based on a competition of best ideas, techniques or strategies (called modes by Synergetics). However, empirically we know very little of these processes. Lo (2004, 2005) used a simple linear autocorrelation model, neglecting nonlinear dependencies. Additionally, a test of market reactions to different types of external or internal influences is missing. Therefore, Strunk (2012, 2019) suggested the development of a method for nonlinear event studies. Relevant market events, like the publication of quarterly financial figures of stock market companies are a well-known research field for the so-called weak form of market efficiency (Fama, 1965, 1970, 1991, 1998, Fama et al., 1969). However the methods used here are linear and very limited seen in the light of modern complexity research methods already discussed above (see Table 1). Based on these considerations, Wagner (2019) from our working group constructed a sound method for nonlinear event studies based on the PD2-method (see Table 1). Non-linear PD2-testing was in every case significantly more precise in the detection of anomalies before the event (publication of quarterly financial figures) and was able to detect such anomalies way earlier than a classical event-study using the same data. Based on different methods (permutation entropy and GEntropies, see Table 1) similar results were found for change of CEOs in German DAX companies (results from our working group: Feigl, 2011, Strunk, 2019).
Based on the framework of Synergetics, disorder-order, order-order or order-disorder transitions can be interpreted as phase transitions induced by exogenous shocks or shifts in order

parameters (e.g. availability of market relevant information on the event). Our research on "early warning signals" in market data is encouraging. Therefore, we think that we are able to offer a better understanding of such "early warning signals" and a deeper insight of how markets are reacting to crises and external shocks by exhibiting variations in complexity.
Therefore, the goals of Working Group C – Economics are:

- Theory building based on efficient market theory, AMH and Synergetics.
- Development of laboratory studies and real world studies on such change processes.
- The extensive testing of sensitivity and specificity of different complexity measurements for the prediction of relevant events and changes in economic systems.
- Empirical and theory-based identification of event classes (e.g. market crises, recurring events etc.) that are accompanied by early warning signals.
- Cooperation with the other working groups in order to reach a deeper understanding of phase transitions in general and methods to predict such dramatic change processes.
- Development of "early warning systems" as applications for real world scenarios.

1.2 Activities and results from other projects

From our network we know that there is a lot of activity in the field of complexity research in Austria, Germany, the Netherlands, Switzerland, and in other countries. However, it is not represented by its own department at universities or other institutions, and as for most active researchers the field is not a core discipline, but rather a theoretical perspective and a toolbox of methods, giving access to formerly unknown or unexplained phenomena of their main field of research (e.g. psychology or business administration). A great portion of complexity research done by our group was realised at departments like "clinical psychology" or "organisation studies, "organisational behaviour" or "economic education" for example. Hence, our scientific community consists of a network of single researchers of various disciplines, located at different institutions all around the world. Though, not institutionalised, this network nevertheless forms a stable system of research cooperation with an output of several hundred papers or books on complexity research. Relevant research papers are cited and marked in the former sections. Due to the limited space given for this application we are able to name just a few central activities and results:

Working group A – Methods: The work on methods for complexity research started in the early 1990s as a cooperation between Prof. Dr. Günter Schiepek (now PMU Salzburg and CCSYS Stuttgart) and Priv.-Doz. Dr. Dr. Dipl.-Psych. Guido Strunk (now Complexity-Research, Vienna, FH Campus, Vienna, TU Dortmund). This cooperation still lasts and together they have written 4 books, and over 60 scientific publications in journals, books and presentations. In the early 1990s software for complexity research methods were unavailable, so Guido Strunk started programming the GChaos software including all algorithms from Table 1 (and lot more) in C/C++ for Windows systems. At first adapted for non-stationary analyses, new methods were developed for small datasets of coarse-grained quality. The Software was extensively tested in cooperation with partners from the industry and in several research projects (the most comprehensive overview is given in: Strunk, 2019). Additionally, GChaos is also used for data analysis in clinical medicine (e.g. Adlbrecht et al., 2010, Adlbrecht et al., 2009). Parts of the software are used in the so-called SNS of Günter Schiepek (e.g. Haken & Schiepek, 2010, Schiepek et al., 2016b, Schiepek et al., 2003, Schiepek et al., 2001). However, there has been no funding for the software, and there are still the research-gaps listed above, which lead to the research goals of group A.

Working group B – Psychology: The work on complexity research in psychology started in the early 1990s as a cooperation between Prof. Dr. Günter Schiepek (now PMU Salzburg and CCSYS Stuttgart) and Priv.-Doz. Dr. Dr. Dipl.-Psych. Guido Strunk (now Complexity-Research, Vienna, FH Campus, Vienna, TU Dortmund). After more than 25 years of work there is now a large database of time series data from therapies available (N>900 therapies with daily data and two single cases with 2,500-3,900 sampling points). Owners of the database are Günter Schiepek (principal investigator), Guido Strunk, Benjamin Aas (LMU München), and Prof. Dr. Wolfgang Aichhorn (PMU, Salzburg). Based on a network of clinics in Austria and Germany data gathering is still going on under the leadership of Günter Schiepek. First results for a limited dataset are in preparation for publication. These publications are conducted by a cooperation (since 2016) with two research groups from The Netherlands (Dr. Anna Lichtwarck-Aschoff, Dr. Fred Hasselman, Merlijn Olthof, Behavioural Science Institute, Radboud University, Nijmegen, The Netherlands and Prof. Marieke Wichers, Dr. Evelien Snippe, University Medical Center Groningen, The Netherlands). However, there has been no funding for the database, and there are still the research-gaps listed above, which lead to the research goals of group B.

Working group C – Economics: The work on complexity research in economics started in 2006 as a cooperation between Prof. Dr. Andreas Liening (TU Dortmund) and Priv.-Doz. Dr. Dr. Dipl.-Psych. Guido Strunk (now Complexity-Research, Vienna, FH Campus, Vienna, TU Dortmund). Additionally, complexity research is an important research issue at the institute for Safety and Security Management, FH Campus Vienna (FH-Prof. Dr. DI Martin Langer) since 2015 and is led by Guido Strunk. Based on both cooperations numerous research activities together with master students and doctoral students are conducted under the supervision of Guido Strunk and Andreas Liening. Some results from doctoral theses were already discussed above (e.g. Kriedel, 2017, Rose, 2017, Sender, 2017, Wagner, 2019). The habilitation treatise of Guido Strunk gives the most comprehensive view on methods of complexity research and examples from economics (Strunk, 2012, 2019). However, there has been no funding, and there are still the research-gaps listed above, which lead to the research goals of group C.

2 BENEFIT AND EXPLOITATION

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2.1 Impact and significance of the project results for the organisations involved in the project

Securing or extending the research position

Complexity sciences in psychology and in economics were fashionable in the 1990s. A lot of theorising about chaos in the brain, “obscure” behaviour of psychiatric patients, management at the edge of chaos, fractal workplaces, chaos in stock markets etc. are published during that time. However, this early phase was characterised by a metaphorical use of theories or of fragments of theories. Empirical methods were embryonic at that time and most of the research in psychology and business administration was published without any empirical findings. First empirical evidence for chaos in psychotherapeutic processes (based on 3922 sampling point from one single psychotherapy) was presented by Günter Schiepek, Guido Strunk and co-workers since 1993 (e.g. Schiepek et al., 1997, Schiepek & Strunk, 1994a, Schiepek & Strunk, 1994b, Schiepek & Strunk, 1995, Schiepek et al., 1995a, Strunk, 2004, Strunk & Schiepek, 2002). Since the early 2000s they were the first to show evidence for phase transitions in psychotherapies (e.g. Strunk, 2004, Strunk et al., 2006). Additionally, in 2005 a working group around Guido Strunk used non-stationary complexity measurements for the first time on financial data and provided evidence for “early warning signals” in such data sets (e.g. Feigl, 2011, Griessmair, 2005, Wagner, 2019). Moreover, GChaos for Windows (www.complexity-research.com) is possibly the only available software for non-stationary and coarse-grained data sets.
However, this work has been done without any funding and by researchers not employed for doing complexity research. Until now, there is no university position named “complexity sciences in psychology” or “complexity sciences in business administration”. We know from many researchers in our field that they are doing complexity research as a hobby besides their main job, like teaching undergraduates in classical linear research methods.
Despite being the first ever to show empirical evidence for relevant complexity research topics, our network is currently not able to work coordinated on the research goals named in this proposal, because it lacks co-workers, time, money and sustainable research positions. Therefore, funding of our proposal will be a significant push forward in order to secure and extend our research position. It will significantly increase our publication output and will enable us to further work on applications (e.g. early warning systems for psychological crises or economic crises).
In short, we argue that we, as researchers from Austria and other European countries, have been in the lead for a long time but are now limited in our capacity and are therefore only able to harvest what we have sowed in the past with support through funding.

The quantitative research output results from publications, which are usual for a PhD (pre doc) and a Habilitation (post doc) in the respective field of research.

2.2 User benefit and exploitation potential

Searching the internet, the term “complexity” seems to be at the heart of an uncountable mass of pages preaching the advent of an increasingly complex world: in January 2019 the phrase “increasingly complex” can be found more than 5 million times on the internet (google search of the exact phrase). This may be one of the reasons, why interest in complexity research and science has risen steadily in recent years. In particular, sudden radical changes, such as the collapse of stock markets or psychiatric, suicidal crises, are experienced as complex events, which are creating a fundamental uncertainty and are therefore inducing similar questions in economics and psychology: how can the emergence of complex crisis-like changes be understood?

However, the term “complexity” is not well defined in most of the popular pages, media, and even scientific papers (Horgan, 1995). Some of the authors do not even seem to be aware of the fact that complexity is the subject of the so-called complexity theories. Based on these theories, complexity can be defined, measured and can be used as an indicator for the stability versus instability of a system’s current state.

Therefore, while complexity itself is defined as being unpredictable, a sudden significant rise in complexity can be an accurate predictor of a dramatic, radical change of the system’s behaviour in the near future. Such radical, disruptive change processes are major challenges for economic systems (e.g. the onset of a financial crises) as well as for human beings (e.g. the onset of a psychological crises).

Based on Synergetics (Haken, 1969, 1990b, Haken & Schiepek, 2010) – one of the most profound complexity theories today – the main hypothesis of our proposal can be formulated as follows:

> The onset of a radical change in complex systems can be predicted beforehand by so-called “early warning signals”, which can be empirically observed by means of a sudden significant rise in complexity.

The goal of this project is to establish three working groups in Austria in order to test and further develop complexity measurements (working group A – Methods) which are able to predict radical change in psychological systems (working group B – Psychology) as well as in economic systems (working group C – Economics).

The possibility to predict and understand the occurrence of disruptive change processes like a psychological crisis or an economic crisis by “early warning signals” could be of great use to economy, politics, society, and the individual. Additionally, the collaboration of methodology, psychology and economics on the subject of sudden changes will be beneficial for all three disciplines. Economic research like behavioural finance for example has already begun to study psychological influences on markets. The human experience of dramatic change can be impelling for further unfavourable market developments. Similar processes could play a role in purely psychological crises as well. In addition, time series analysis has a long tradition in economics, which can be beneficial for Psychology. Particularly event studies, known from economics, can be used as templates for analysing psychological events. Furthermore, both disciplines are in need of methods able to handle the limited and at times inaccurate data collected in the field.

First positive results from our working group are encouraging. However, in a second step we have to improve and test different methods for different change processes. Therefore, the goal is to give an evidence based overview of those methods. This can be seen as a table with change processes as rows and methods as columns. Sensitivity and specificity as results of testing with empirical data and with simulated data sets are located at the table's cells. This step is of great importance for future research and will hopefully encourage a worldwide search for the best "early warning signals" based on complexity methods. Hence, our search could be the start of a new research paradigm.

Additionally, identifying the best "early warning signals" could be of use to build "early warning systems" for selected change processes. However, this is a third step and needs additional research for e.g. other determining factors and the interplay between complexity based warning signals and non-complexity based signals. Therefore, an "early warning system" has to include more variables than just complexity measurements and must be grounded on theories of the respective field (psychology and economics in our case). Therefore, our network not only consists of scientists but also of real-world clinicians, management consultants etc. This ensures that a) data is being collected in real world settings, b) questions addressed have real world relevance and c) appropriate valorisation and knowledge translation to real world settings is guaranteed.

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