LEVERS OF EMERGENCE: A GENERIC FRAMEWORK OF COMPLEX ADAPTIVE SYSTEMS IN MANAGEMENT SCIENCE

Meike Tilebein
Research Associate
Universität Stuttgart, BWI Abt. IV, Keplerstr. 17, 70174 Stuttgart, Germany
E-mail meike.tilebein@bwi.uni-stuttgart.de, www.bwi.uni-stuttgart.de/planung

Résumé : Les entreprises agissantes en période de concurrence dynamique doivent équilibrer l'efficacité et l'innovation. La science de complexité est une approche interdisciplinaire à des systèmes qui produisent ces deux qualités d'une manière émergente. Ces systèmes s'appellent systèmes adaptatifs complexes. Sur la base des résultats de la science de complexité concernant les phénomènes émergents, nous développons dans cet article un modèle général de systèmes adaptatifs complexes pour l'utilisation dans la gestion d'entreprise. Ce modèle montre les instruments qui évoquent des effets émergents. À l'aide de notre modèle, nous examinons des applications existantes de la science de complexité à différents niveaux de l'entreprise. Nous analysons les effets émergents souhaités et les instruments utilisés pour les obtenir. Nous montrons que notre modèle peut aider à soutenir les processus d'émergence dans les entreprises.

Abstract : Companies acting in times of increasingly turbulent competition have to permanently balance efficiency and effectiveness. Complexity science provides an interdisciplinary theoretical approach for studying systems that emergently exhibit these two properties. Such systems are called complex adaptive systems. In this paper we propose a generic framework of complex adaptive systems in management science that is based on complexity science's theoretical insights on emergence. The framework shows the levers of emergence in firms. We use it to examine examples from the literature that apply ideas from complexity science to different organizational levels. Applying our framework to each example, we analyze the desired emergent properties and the corresponding levers of emergence. We conclude our framework serves to both analyze and integrate efforts to support processes of emergence in companies.

1 Introduction

Companies in many industries are acting in turbulent environments, in which conditions permanently change, competition increases, and foresight is limited to the very near future. In the face of such turbulences, two problems become especially urgent.

First, the characteristics of turbulent environments make it difficult to manage firms top-down. This accounts for management science's increasing interest in bottom-up approaches, some of which are based on the idea of emergence.

Secondly, in turbulent environments the old dilemma between efficiency and effectiveness is pressing. Firms can achieve short term success by improving efficiency. However, in order to successfully survive in changing business landscapes in the long run, they have to be innovative. Hence, it is crucial to permanently balance the conflicting forces of efficiency and effectiveness. A final solution to this dilemma is still pending.

In recent years there has been a growing literature on how to resolve these two problems by applying insights from the field of complexity science. Complexity science provides an interdisciplinary theoretical approach for studying large systems that exhibit emergence, for example ant colonies, ecosystems, big cities, bird flocks or markets. The term "emergence" describes the generation of macro-level system properties arising from micro-level interactions of system elements without being planned or foreseen. Complexity science searches for common underlying principles of such systems that are called complex adaptive systems (Gell-Mann, 1995). It has its roots in e.g. systems theory, evolutionary biology, game theory and information science.

According to complexity science, complex adaptive systems (CASs) typically show two kinds of emergent properties: emergence of innovation due to evolution over time and emergence of spontaneous order. Furthermore, they exhibit adequate combinations of these emergent properties. This is why CASs are able to emergently change, adapt and (co-)evolve in harmony with their changing environments. Hence, emerging properties make CASs sustainable as a whole although such systems generally do not have a system-level control.

As these characteristics of CASs perfectly match with the requirements of companies in today's turbulent environments, management science has shown increasing interest in CASs recently. Many books and papers have been published that apply principles of CASs to firms in order to generate emergent properties. Applications cover the entire span of organizational levels and a broad scope of goals.
Nevertheless there is still a gap between CAS theory from complexity science and CAS applications to firms. Complexity science uses simple computer-based models to explain the basic underlying mechanisms of emergence in CASs in a very general and abstract way. In contrast, applications of CAS principles to firms mostly address very specific problems on selected organizational levels, without seeing the organization as a whole. In other words: while CASs offer a valuable new theoretical perspective on emergence in general, their application to management science still suffers from a lack of integration and is too fragmented to yield practical results.

In this paper we propose a generic framework of complex adaptive systems in management science that shows the levers of emergence in firms. In order to develop this framework, we first give a brief outline on CAS models used to explain emergence. Based on these results we propose our framework. We then use this management-science CAS framework to analyze and evaluate examples from the literature transferring ideas from complexity science to management science. We examine exemplary applications on four organizational levels: the individual resource level, the organizational sub-unit level, the organizational level and the network level. Applying our framework to each application, we analyze the desired emergent properties and the corresponding levers of emergence used.
As a result, we show that there is a wide range of CAS applications to firms with different focus. Typically they address either emergent innovation or emergent order and thus fail to combine effectiveness and efficiency. We conclude our framework may serve to integrate such applications towards a better understanding of firms' levers of emergence.

2 Models of Emergence in Complex Adaptive Systems

This section briefly summarizes characteristics of CASs and prominent models of emergence. There are two kinds of emergent properties in CASs: spontaneous order accounting for efficiency and flexibility, and innovative evolution. Complexity science uses abstract computer-based models to study these emergent phenomena in CASs.

2.1 Basic Characteristics of Complex Adaptive Systems

A CAS is a network of elements, whose interactions cause the emergence of overall system level properties. Real examples of complex adaptive systems are ecosystems, bird flocks, ant colonies, the nervous system or man-made systems like industries or big cities. Although very different in detail, CASs have common characteristics (for different models of CASs, see e.g. Holland, 1995; Gell-Mann, 1995; Kauffman, 1993; Auyang, 1998). Basic components of a CAS are active elements, called agents (Holland, 1995). Agents can combine to meta-agents which, in turn, can form even more aggregated agents, a CAS can be an agent of a network, and so forth: CASs can form a (temporary) structure following a “box-in-a-box” principle (Simon, 1996). Each agent acts according to an individual set of rules that is called schema (Holland, 1995). An agent has a limited number of direct interaction partners. The self-organization of interacting agents gives rise to emergent phenomena in a CAS.

2.2 Models of Emergent Order

Cellular automata are widely used to study the emergence of spontaneous order in rule-based systems. They are computer-based spatial systems of cells that change their state (e.g. black-white) according to a given transformation rule. This rule determines a cell’s next state dependent on the actual states of a number of neighbouring cells. This way spatial patterns unfold over time. Depending on the rules, different static or dynamic patterns emerge (Wolfram, 1994; Wolfram, 2002).

Boolean networks (Kauffman, 1993) are a second class of models of emergent order. In these models agents are mutually linked Boolean functions that form a network. According to Kauffman (1993) self-organized Boolean networks settle to attractors that can either be chaotic, or frozen, or balanced states with both stable clusters and changing regions. In this balanced state on the so-called “edge of chaos” a network reaches a maximum in information processing capacity, it can display spontaneous order and absorb external disturbances (Langton, 1992). The character and diversity of the functions used and the number of their inputs determine whether a Boolean network operates on the edge of chaos.

Another prominent model of rule-based interaction is called “boids”. In this computer based simulation of a bird flock three rules, concerning speed, distance, and relative flight direction, control the motion of the individuals called boids. (Reynolds, 1987). Based upon these rules, boids show bird-like behaviour in forming flocks and performing flight manoeuvres. Although boids are uniform agents with a fixed set of rules for interaction, the bird flock as a whole can react to unforeseen disturbances like obstacles in the way. This kind of emergent order is known as “swarm intelligence” (Bonabeau, Dorigo, & Theraulaz, 1999).

2.3 Models of Emergent Innovation and (Co-)Evolution

NK models (Kauffman, 1993) are used in complexity science to study evolution and innovation. Agents in these models consist of N elements (e.g. properties, genes, or other attributes). Each element can take on two different values, 0 or 1. To each of the two values of every one of the N elements a fitness contribution is (randomly) assigned. Agents can evolve and improve their overall fitness by switching values of elements one by one, in a process called “adaptive walk”. A fitness landscape visualizes the overall fitness function. There are three different types of fitness landscapes: single-peaked landscapes with one global fitness maximum, multi-peak landscapes with random peaks, and moderately rugged landscapes with correlated peaks (see Figure 1).

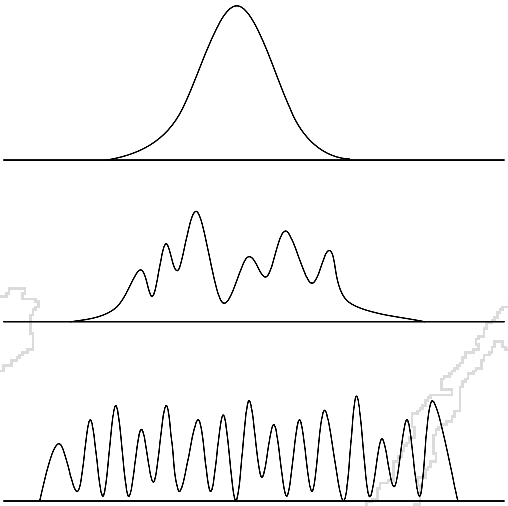

Figure 1: Types of fitness landscapes

As the direction of an adaptive walk has to be uphill per definition, in single-peaked landscapes adaptive walks always lead to the global maximum, whereas in a multi-peak landscape they end on the local maximum nearest to the starting point. Once the agent has reached a local peak it cannot improve any more, although there might be a higher peak in some other region of the fitness landscape. Diversity eventually evolves in a population of formerly identical agents when their random adaptive walks take different directions.

The parameter K in NK models affects the shape of the fitness landscape. K is the number of epistatic links between the N attributes of an agent, that is the number of other elements influencing that attribute. If the fitness contributions of the N elements are independent (K=0), the agent's overall fitness equals the sum of all N fitness contributions. In this case improvement in one element improves the agent's overall fitness likewise. Thus, a single-peaked fitness landscape is generated. In contrast, if the fitness contribution of an element depends on the value of K others, a landscape with more peaks is formed. The number of peaks increases with K.

Coupling of agents results in coevolution, when evolving agents affect each other. In coevolution an agent's fitness landscape is not static, but it may change with every step another agent takes. In other words, the ground is moving. This can be a disadvantage for agents walking in single-peaked landscapes, as they might never reach the moving peak. For agents stalled on lower peaks in multi-peak landscapes however, a landscape change may put them off that local peak and into a new starting position. Therefore, in a coevolutionary scenario moderately rugged fitness landscapes (K=2) are most advantageous for individual agents.

To study coevolution, NK models are extended to NKSC models (Kauffman, 1993), where S is the number of species coevolving and C is the number of links between each pair of species. These parameters determine external complexity, just as K determines internal complexity. Coupled CASs coevolve to the edge of chaos, with a maximum average fitness of agents and a dynamic stability of the overall system, when internal and external complexity are balanced.

3 A Generic Framework of Complex Adaptive Systems in Management Science

In real CASs, like biological systems, there is no system-level control and thus there is no intentional system design. These systems emergently self-organize and evolve towards the edge of chaos, where average fitness and chance of system survival reach their maximum. In abstract CAS models however, conditions for self-organizing agents can be deliberately set. From the previous section a number of interdependent properties of CASs can be identified that are prerequisites for emergence in these systems. We first give a short summary of these levers of emergence and then merge them to characteristics of companies in order to develop a generic framework for levers of emergence in firms.

3.1 Levers of emergence in Complex Adaptive Systems

Complexity science's experiments with evolutionary models, cellular automata, Boolean networks and other rule-based interaction systems reveal that a set of parameters act as levers of emergence in such systems:

Agents: As stated above, agents are the core elements of complex adaptive systems. When designing a CAS, agents have to be defined adequately. In a general definition, an agent is an active element of a CAS. Agents interact with one another based on a set of rules. In many CAS models, agents are simple switches.

Properties: In the models used in complexity science agents' properties or attributes are often conceptualized as a number of elements that can take on different states or values. NK models show that the number of elements and the number of links between these elements influence emergence.

Diversity: Agents in a CAS can be uniform or diverse in their properties and rules. Diversity evolves from self-organization when agents are adaptive, with each agent adapting individually to its local network or niche, as in the NK models. In contrast, diversity can be set by shaping properties and rules of agents in a system where agents are fixed and non-adaptive, as in the boids model.

Action rules: Rules are a prominent part of agents' properties. Action rules describe information processing procedures. In complexity science's models, rules are Boolean functions or other mathematical algorithms. Emergence in Boolean networks depends on the character and diversity of the functions used and the number of links between agents. If these two parameters are set properly, dynamic structures emerge in a network. Interacting agents can form (temporary) meta-structures, depending on their interaction rules and the number of their interaction partners. These aggregated agents can act as agents themselves. This way, a CAS shows a "box-in-a-box" structure.

Change rules: Rules, properties, and links in a CAS structure can be fixed or subject to changes made by adaptive agents. For agents to be adaptive, change rules have to be defined in order to get variations in agent properties, links and rules. The adaptive walk implemented in NK models is a change rule that allows agents to change one property at a time.

External links: The number of external links connecting an agent with others characterizes the density of the resulting network. Experiments with cellular automata and Boolean networks demonstrate that, depending on the density, agents' self-organization processes and the emergence of effects on the overall system level will be rather supported or blocked respectively. External links account for coevolutionary dynamics in a system of coupled adaptive agents.

Internal links: The number of internal or epistatic links is a measure of an agent's internal complexity. When an agent's properties are coupled via internal links, their contributions to the agent's overall fitness are not independent; this way a change in one property can affect fitness contributions of others, too. Fitness landscape models are used to characterize change processes of adaptive agents. These agents perform hill-climbing adaptive walks in their individual fitness landscapes, each trying to reach a point of maximum fitness. Depending on the shape of the fitness landscape, which in turn is influenced by internal links within the agent, adaptive walks will be more or less successful. As agents are linked to each other via external links, their fitness landscapes are coupled, too. As a result, an agent's fitness landscape gets dynamic with coevolution. Landscape peaks shift when changes in other agents occur.

3.2 Levers of Emergence in Firms

In the following we propose a generic framework of CASs for use in management science. Firms differ from the CAS models described above as they have a system-level control on different organizational levels. Hence, their characteristics often are subject to deliberate intervention rather than random change. This is why we add two levers of emergence to those identified in the previous section: First, we see fitness landscapes as one of the levers of emergence in firms. Whereas complexity science assumes fitness landscapes to be set randomly by internal links, goal-setting is an important activity in management. Secondly, aggregation of agents is a crucial management task. Whereas agents in CAS models self-organize to form temporary structures and meta-agents, organizational structure in firms is defined and changed by management.
In the following we give an overview of the resulting nine levers of emergence in firms. Put together, these form a generic framework of emergence in complex adaptive systems in management science, as proposed in Figure 2.

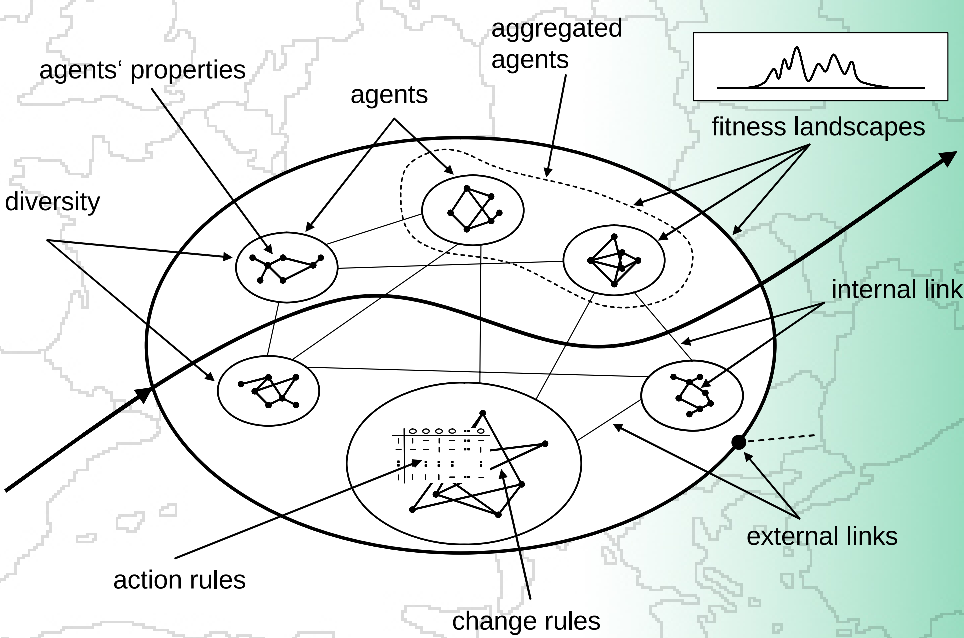

Figure 2: A generic framework of complex adaptive systems in management science

1. Agents: In management science, agents' equivalents can range from individuals to firms. Their classification depends on the purpose of CAS applications.
2. Aggregated Agents: In management science such aggregations can be e.g. departments or networks. In most cases they don't form by themselves, but they are defined by management.
3. Agents' Properties: Relevant properties of agents depend on the application purpose and the nature of the agents. CAS models reveal that the number N of properties is important.

4. Action Rules: In a CAS all agents' interactions are based on rules. Action rules describe an agent's information processing procedures. In firms, they range from simple if-then-rules to mental models in human decision-making.
5. Change Rules: If agents are allowed to change on their own initiative, they need change rules. In firms, change is usually restricted in terms of resources, scale, scope etc.
6. Diversity: Diversity evolves from learning and self-organization or diversity is set by shaping agents' properties and rules, e.g. by staffing teams or by allocating different resources to production lines.
7. External Links: Depending on the density of the agents' network, self-organization processes and the emergence of qualities on a higher level will be rather supported or blocked respectively. A company's external links are e.g. communication links, or interfaces in production processes, or customer relationships.
8. Internal Links: Internal complexity affects the potential overall system fitness. Firms can actively design internal complexity, for instance by reducing internal links with the help of product and process modularization. According to the box-in-a-box organization of CASs, the definition of internal and external links depends on the level of observation.
9. Fitness Landscapes: Fitness landscapes in management science can be e.g. incentive systems, or performance measurement systems. In addition, organizations can affect their own fitness landscapes by establishing external links to partners and competitors, and by designing internal complexity.

4 Using the Generic Framework to Analyze Business Applications of CASs

CASs have been applied to a number of management science problems on different organizational levels, ranging from individual to industry level. Beside the differences in application levels there are also differences in objectives: Whereas some of the transfer concepts stress emergence of efficiency, others aim at emergent innovation. In the following, we distinguish four organizational levels - the individual resource level, the organizational sub-unit level, the firm level and the network level. Starting with the individual level, for each level we examine two exemplary applications of CAS principles with different focus and objectives.

4.1 Individual Resource Level

On the individual resource level (R), insights from CASs are adopted to explain the emergence of knowledge, culture, or meaning. For instance, "memes" (Dawkins, 1989), that are society's equivalent of genes, can be seen as agents that interact to build culture or knowledge. Agents can be e.g. ideas, scientific theories, or pieces of music. They are located in individuals where they compete for attention (Marion, 1999; Blackmore, 2001). This concept is based on the diversity of agents and on selective fitness landscapes.
The concept of complex responsive processes (Stacey, 2001) focuses on the interaction processes that enhance the emergence of knowledge. Here agents are elements of knowledge, called symbols. Meaning is ascribed to these symbols via interaction and communication processes. In this view, knowledge is an emergent property of a communication process. Rules and internal links are the levers of emergence this concept addresses.

4.2 Organizational Sub-Unit Level

On the organizational sub-unit level (SU) there are some concepts that aim at emergent order and others that aim at emergent innovation. Applications aiming at emergent order and efficiency use swarm intelligence and agent-based systems (Bonabeau, Dorigo & Theraulaz, 1999; Macready

& Meyer, 1999; Bonabeau & Theraulaz, 2000). The basic idea is to provide agents (that can be technical resources of any kind or even humans) with a fixed set of rules and objectives for their interaction and then let them self-organize according to the given rules. Properly set, the overall system will display emergent order, it will be robust in the face of disturbances and it will be able to respond to unforseen changes. Swarm intelligence is used in resource allocation processes to replace conventional optimization procedures that are of limited use when faced with dynamically changing problems. In these concepts agents and their properties as well as action rules are used as levers of emergence.

Aiming at emergent innovation, Allen (1997; 2001) uses coevolutionary simulation models to study emergence of knowledge. Agents in these models can be either individuals or groups. Allen stresses the fact that learning opportunities and mistakes are sources of innovation when communication structures are shaped properly. In terms of levers of emergence, the concept thus focuses on diversity, external links and change rules.

4.3 Firm Level

On the firm level (F), there are applications similar to those on sub-unit level that use agent-based systems to efficiently manage production processes. One application e.g. dynamically restructures a production-process layout using an agent-based system with mobile resources as agents (Wiendahl & Harms, 2001).

However, most of the firm level applications aim at emergent innovation, e.g. in strategies, technologies, projects or organizational knowledge. Often they use NK models (Caldart & Ricart, 2004). One application links the emergence of strategies to organizational structure and information processing (Boisot & Child, 1999; Boisot, 2000). This concept uses diversity (cognitive complexity) and internal links (relational complexity) as levers of emergence.

4.4 Network or Industry Level

On the network level (N), applications use agent-based technologies to improve efficiency of interorganizational production and supply chain management. Other order-oriented applications analyze the emergence of industrial districts (Rullani, 2002). In all of these applications, agents are firms, and the emergent results of their interactions are efficient processes or structures. Action rules, external links and fitness landscapes serve as levers of emergence.

In addition, CAS models aimed at innovation have been used on this level to foster competitive advantage. In a model-based application, Kauffman's NKSC studies are applied to firms in coevolving networks (McKelvey, 1999), with a focus on balancing internal and external links.

5 Discussion and Conclusion

CASs exhibit emergent effects in terms of spontaneous order and innovative evolution. In this paper we sketched out basic ideas of CASs and proposed a generic framework for emergence in firms to analyze exemplary applications of CAS principles to different organizational levels (for an overview, see Figure 3). From this analysis we conclude that complexity science is not yet ready to offer a comprehensive bottom-up solution to the efficiency-effectiveness dilemma in turbulent environments for three reasons:

1. Whereas in theory a CAS should be capable of both emergent order and emergent innovation, concepts transferring these findings into firms are fragmented into two basic streams: One stream attempts to make use of the self ordering properties of complex adaptive systems. Examples are applications of "swarm intelligence" and agent-based technologies. A second stream is based on NK models and strives to transfer insights concerning coevolution and emergent innovation of CAS to different organizational levels.

2. Each application employs only a few out of the nine levers of emergence identified in our generic framework. None of them thus makes use of the full potential of a CAS.
3. There are no multilevel models so far. Applications span a wide range of organizational levels. However, most applications take into account only two organizational levels, one agent level and another level where the desired emergent effects arise.

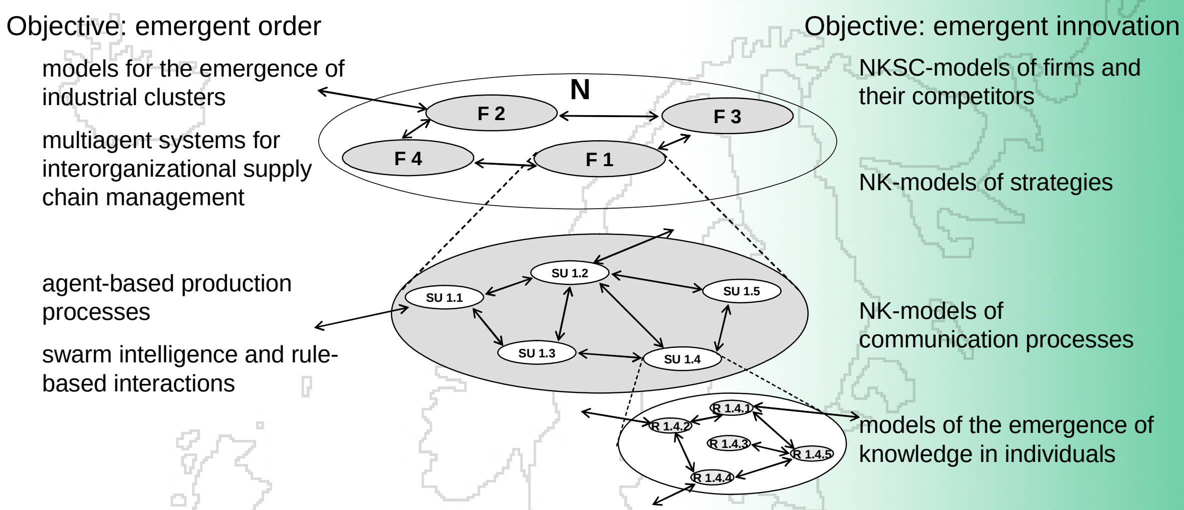

Figure 3: CAS applications on different organizational levels

In spite of the shortcomings of CAS applications listed above, we observe two aspects in favour of a further CAS approach to emergence in firms:
1. CASs can contribute to a deeper and integrative understanding of the multiple issues involved in emergence of innovation and efficiency on all organizational levels.
2. For different organizational levels and specific problems applications of CAS principles already exist. Efforts towards integration should be undertaken.

We conclude that complexity science is far from generating a ready-to-use concept to support emergence in management science. However, insights in CASs can reveal the necessary conditions to manage the conflicting forces of efficiency and effectiveness in today's turbulent business environments with the help of emergent effects. The proposed generic framework of complex adaptive systems in management science may serve to analyze, evaluate and integrate CAS applications to firms, towards a better understanding of firm's levers of emergence.

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