SILESIAN UNIVERSITY OF TECHNOLOGY PUBLISHING HOUSE

SCIENTIFIC PAPERS OF SILESIAN UNIVERSITY OF TECHNOLOGY 2023
ORGANIZATION AND MANAGEMENT SERIES NO. 189

STUDY OF EMERGENT PHENOMENA IN THE ORGANIZATION

Agnieszka KOWALSKA-STYCZEŃ[1*], Vasyl LYTVYN[2]

[1] Silesian University of Technology, Faculty of Organization and Management;
agnieszka.kowalska-styczeń@polsl.pl, ORCID: 0000-0002-7404-9638
[2] Lviv Polytechnic National University, Information Systems and Networks Department;
Vasyl.V.Lytvyn@lpnu.ua, ORCID: 0000-0002-9676-0180
* Correspondence author

Purpose: The aim of this article is to draw attention to the specificity of emergent phenomena in organization and management, the study of which requires an approach derived from complex adaptive systems.
Design/methodology/approach: The article uses a critical analysis of research on emergent phenomena in organizations from the perspective of complex social systems. This analysis made it possible to distinguish types of emergence in organization and management depending on the type of agents (members) and interactions that take place in the organization and indicated the causes of emergent phenomena.
Findings: The article creates a research framework for complex emergent phenomena and shows how to use computer simulation to study complex emergent phenomena in organizations.
Originality/value: A relatively new direction of research are analyzes within the theory of complex adaptive systems, the aim of which is to model and explain the behavior of systems of interconnected objects based on knowledge about the laws of individual elements (at the local level) and the structure of their connections. Therefore, it seems interesting to use computer tools developed based on complexity theory, especially agent-based models, as proposed in this article to study emergent phenomena in organizations. Since there are many approaches and ways of using computer simulations to study complex adaptation phenomena, a method of creating a simulation model and a method of conducting research using it were proposed.

Keywords: Emergent phenomena, Complex adaptive system, Organization and management, Agent-based models.

Category of the paper: Research paper, Literature review.

1. Introduction

Today's organizations are complex systems that consist of heterogeneous elements that interact with each other and with the environment that are difficult to understand, predict and control. Their characteristic feature is the ability to exhibit complex emergent properties.

This means that it is difficult to predict the effects of micro-level interactions on the system (organization) as a whole, even if the behavioral patterns of individual agents are known. However, usually the effect of interaction at the micro level is adaptation towards changes that will ensure survival in the environment and on the market. Moreover, in organizations, people or groups adapt to feedback on the behavior of others and act without clear coordination and central communication (Anderson, 1999; Maguire, McKelvey, 1999). Organizational members often form informal groups that function through local interactions without central control or management

Understanding and managing the internal complexity of an organization therefore requires strategies that go beyond traditional analytical methods. A new way of examining processes taking place in an organization is agent-based simulation (ABS) (Gotts et al., 2003). ABS allows you to recreate interactions between people within an organization or between organizations in a marketplace to assess the aggregate outcome of their behavior. The basis for studying organizations from the perspective using ABS is an attempt to explain the behavior of the entire system (at the macro level) based on the recognition of the rules of behavior of its components (micro level).

In this article, the concept of emergence from the theory of complex adaptive systems (CAS) is used (Kauffman, 2000; Axelrod, 1997; Axelrod, Cohen, 2000; Bonabeau et al., 1999). This approach is consistent with the proposed method of studying social phenomena in organizations based on computer modeling. The basis for researching organizations in the context of CAS is the perception of organizations as a complex social system. Numerous studies in the field of social sciences indicate that individuals are embedded in the networks of social relations and interactions (Borgatti et al., 2009).

According to Plsek and Greenhalgh (2001), CAS is a collection of individual agents with freedom of action, which is not always entirely predictable. In addition, agents are so connected to each other that the behavior of one agent changes the context for other agents. As emphasized by Mille and Page (2007) in CAS there are therefore units at the micro level that, through mutual interactions, form global system properties, which then, by feedback, affect the interaction at the micro level. In addition, CAS through interaction with the environment modifies its behavior, adapting to changes in the environment (Rammela et al., 2007; Rotmans, Loorbach, 2009). This behavior of the system is a manifestation of its adaptability. Complex adaptive systems are also characterized by emergence (Mitleton-Kelly, 2003). The system has emergent properties if its presence is new at the evolutionary level or at the physical level of the complexity of the system in which it occurs (Newman, 1996). It is the emergence of new and consistent structures, patterns and properties in the processes of self-organization occurring in complex systems (Goldstein, 1999). In the case of organizations or organizational management, it is difficult to predict the effects of interactions at the micro level for the organization as a whole, even if the behavioral patterns of individual members (elements) of the organization are known. The behavior of the organization as a whole is emergent.

It should also be noted that in such systems rules at the local level, i.e. at the level of individual units or networks of units, as well as the way they interact, are often more important than global directives. In addition, as Sanders and McCabe (2003) show, understanding of the local dynamics of the system can allow insight into the behavior of the entire system and help identify key reasons for changes and transformations.

The aim of this article is to draw attention to the specificity of emergent phenomena in organization and management, the study of which requires an approach derived from complex adaptive systems. Such an approach is computer simulation based on agents. The article shows that emergent phenomena, depending on agents/individuals and system behaviors/interactions, may occur at four different levels. Moreover, it was shown that ABM is an appropriate tool for examining emergent phenomena.

2. Emergent phenomena in the organization

Emergence is the formation of new and coherent structures, patterns and properties in self-organization processes occurring in complex systems (Goldstein, 1999). Checkland (1981) defines emergent properties as those emerging from the system of human activity as a single whole, which results from the activities of the components and their structure, but cannot be reduced only to them. Emergence is, therefore, the appearance of properties that have not been previously observed in the behavior of the system and which cannot be reduced to the properties of its individual components.

In complex adaptive systems, we can distinguish behaviors that influence the phenomenon of emergence (Plowman et al., 2007; Lichtenstein, Plowman, 2009). In such systems, global changes are generated based on local behavior, which in turn change local behavior (Burkhart, 1996). By interacting with and learning from the environment, a complex adaptive system modifies its behavior to adapt to changes in the environment (Rammela et al., 2007). The adaptability of CAS therefore lies in the ability to change and learn from experience, i.e. these systems can respond and adapt to changes occurring in their environment (Rotmans, Loorbach, 2009). Adaptability in CAS is, of course, a manifestation of emergence, which is visible in modifications of behavior under the influence of the environment, adapting the system to the requirements set in the environment. These modifications are made thanks to appropriate interactions, which are intense, non-linear and contain feedback. A special role here is played by the openness features of the system, i.e. appropriate opportunities and methods of interaction with the surroundings (environment).

Fundamental changes generated by these interactions are implemented in subsequent stages of system functioning thanks to processes defined as coevolution and self-organization (Mitleton-Kelly, 2003). Adaptive movements of individuals are the effects of agents' interactions (e.g. changes in attitudes, views, level of knowledge, etc.) referred to as coevolution. The effect of these changes at the level of the entire adaptive system (macro level) is co-evolution with its environment, i.e. responding to changing external requirements (Mitleton-Kelly, 2003). One of the effects of co-evolution is self-organization, i.e. a phenomenon in which the elements of a complex system become spontaneously ordered. This ordering is the result of independent interactions between individual agents within the system and/or agents and the environment (Mainzer, 1994). Self-organization therefore refers to the ability to develop a new system structure resulting from the internal structure of the system and its interaction with the environment, but not the external management of the system.

Taking into account the specific characteristics of CAS behavior, it can be concluded that most organizations are characterized by a set of attributes and special behaviors typical of adaptive complex systems. First of all, an organization, is perceived as a group of people, i.e. related elements (agents) interacting with each other in various ways. These interactions are rather intense and non-linear (with many feedback loops), which means that each member of the organization influences many others and vice versa, and the influence of even one person or small group can cause significant changes in entire spheres of the organization's activity (e.g. innovations, knowledge, culture, leadership, etc.). Moreover, organizational members also react to information flowing directly or indirectly from the environment.

The behavior of the organization as a whole is emergent because it is difficult to predict the effects of micro-level interactions on the organization as a whole, even if the behavioral patterns of individual agents are known. Usually, however, the effect of interactions at the micro level is co-evolution towards changes that will ensure survival in the environment and on the market.

As Lichtenstein and Plowman (2009) emphasize, emergence in an organization is the result of interactions between a group of agents - individual members and managers, networks and organizations. Even relatively simple elements interacting may generate new and surprising behaviors, which make it impossible to predict future states (Bohórquez Arévalo, Espinosa, 2015). As shown above, the main causes of emergent phenomena taking place in the organization are adaptability, co-evolution, feedback and states far-from-equilibrium, as shown in Table 1.

In the study of emergent phenomena occurring in social systems, types of emergence can be distinguished due to the complexity of agents (individuals) and the systems themselves (Lichtenstein, McKelvey, 2011). Individuals can be homogeneous or heterogeneous. The complexity of a system, on the other hand, can be determined by the interactions and behaviors that take place in the system. The interactions may be non-linear and the system may operate in conditions far from equilibrium, or the interactions may be linear and the system may operate in equilibrium conditions. Taking these dimensions of complexity into account, four types of emergence can be identified. Taking these dimensions of complexity into account, four types of emergence can be identified (Fig. 1).

Table 1.
Causes of emergent phenomena in the organization and management

Cases	Definition/Study	
Adaptability	Heterogeneous, autonomous individuals have the ability to learn from experience, which gives them the ability to respond and adapt to changes in their environment (Rotmans and Loorbach, 2009).	
Co-evolution	Usually, the effect of interactions at the micro level in an organization is co-evolution towards changes that will ensure survival in the environment and on the market (Ferloni, 2022; Quitzow, 2015; Edmonson et al., 2019)	
Feedback	Feedback in human interactions means influence that changes (strengthens or weakens) potential actions and behaviors (Mitleton-Kelly, 2003) Individuals influence each other, either directly or through feedback loops that continually evolve and adapt to achieve overarching goals (Sanders, McCabe, 2003)	individuals influence each other, either directly or through feedback loops that continually evolve and adapt to achieve overarching goals (Sanders, McCabe, 2003).
Far-from-equilibrium	This is due to the characteristics of interaction processes, which are, by definition, dynamic (variable at each step and dependent on each step). A state of equilibrium would mean the absence of interactive processes. (Meyer et al., 2005)	

Source: own study.

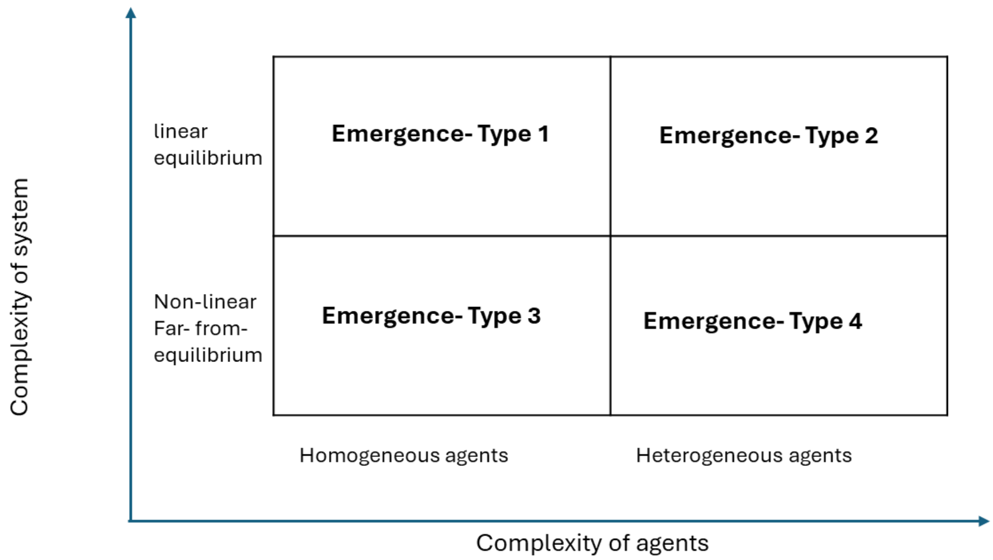

Figure 1. Typology of emergence.

Source: own study based on Lichtenstein and McKelvey (2011).

As can be seen in Figure 1, Type 1 emergence occurs when agents are homogeneous and the interactions between them are linear. Examples of research on such emergence concern primarily group behavior (Granovetter, 1978, Macy, 1991), emerging structures of behavior in social networks (Burt 1992), competitive advantage (Porter, Siggelkow, 2008), entrepreneurship and start-ups (Ganco, Agarwal 2009); technological innovation (Flemming, Sorenson, 2001).

It should be noted that Type 1 research on emergence covers the interactions between elements and the structure of the system to the smallest extent. Research taking into account emergence focuses here on the properties of the system; the nature of the whole can be known by deduction based on knowledge about the nature of its components.

The second type of emergence (Type 2) concerns heterogeneous agents and linear interactions. In this case, the emergent property or structure is defined as "different in kind" from it ingredients. The elements of an emerging strategy arise from interactions at the individual and group levels (human, social and relational capital). Agents become increasingly complex as the hierarchical relationships between parts and wholes become more intense. Examples of research on such emergence include the creation of emergent strategies (Nonaka, 1994); self-organization based on simple rules: urban segregation (Schelling, 1978); alliances and other group formations (Axelrod et al., 1995).

In the third type of emergence (Type 3), agents are homogeneous, but interactions are nonlinear and occur in states far from equilibrium. Co-evolution and self-organization as well as adaptation take place. What emerges at the macro level of a system can causally influence its elements, changing the behavior of its parts, while the parts (elements/units) simultaneously change the nature of the larger whole (Thomas et al., 2005). Research also concerns emerging institutions, for which it is examined how structures at the macro (institutional) level supervene on behavior at the micro (individual) level (Contractor et al., 2000).

Examples of research at four levels of emergence that concern management and processes taking place in the organization are presented in Table 2.

Table 2.
Examples of research for four types of emergence in organization and management

Emergence	Study
Type 1	Self-organizing criticality: - most job changes generate very small vacancy chains, but sometimes one job change can trigger a large cascade of subsequent changes in the organization (Gunz et al.; 2001) - propositions about emergent leadership (Lichtenstein, Plowman, 2009) - examples of SOC in economic and financial markets (McKelvey, Salmador Sanchez, 2011)
Type 2	Simple rules for agents lead to self-organizing behavior: - a model of urban segregation based on the cellular automata (Schelling, 1978) - agent-based models (cellular automata) for studying word of mouth marketing (Kowalska-Styczeń, Sznajd Weron, 2012) - a spatial simulation model in which business activities, initially randomly dispersed, always evolve into a highly ordered distribution around a central business district (Krugman, 1996)

Type 3	The use of genetic algorithms: - simulation of an organization consisting of agents (Crowston, 1996) - model adaptations to organizational structure by examining the adaptation of financial trading firms (Paul et al., 1996)	individuals influence each other, either directly or through feedback loops that continually evolve and adapt to achieve overarching goals (Sanders & McCabe, 2003).
Type 4	Simulation on many levels: - a four-level simulation that consists of small groups interacting employees (agents) led by an executive team that develops firm-level strategy based on environmental inputs (Carley and Lee, 1998; Carley, 1999a) - agent-based model (ABM) including cellular automata, genetic algorithms and neural network for stock-market trading (Lebaron, 2000)	

Source: own study.

3. Tools for examining emergent phenomena in organizations

Choosing the right way t to research and analyze emergent phenomena in an organization, attention should be paid to the limitations caused by the nature of such systems. These limitations are as follows:

- a large number of basic elements of such systems (agents/ individuals), hence also a large number of interactions,
- the high complexity of real organizations/institutions (study too many aspects at the same time is actually not possible),
- the need to take into account changes in time, limits the ability to analyze the dynamics of real-world behavior in the long-term.

As Table 2 shows, the most frequently used approach to studying emergent phenomena are agent-based models (ABM), including cellular automata (CA). Agents (actors) in such models (as in real social systems) interact and influence each other, learn from their experiences and adapt their behavior to the environment (Macal, North, 2010). They can represent people, but also companies, organizations or states. Moreover, as Artime and De Domenico (2022) emphasize, in ABM, when interactions occur between individual agents, emergent phenomena occur, consisting in the spontaneous emergence of surprising results at a higher level of aggregation that could not be predicted at the model construction stage.

To create an agent-based model describing a phenomenon, the following elements must be defined:

- Goal.
- Agents.
- Properties, attributes for agents.
- Rules for agents.
- Simulation steps and duration of the simulation.
- Model verification and validation.

Therefore, the construction of ABM requires a thorough understanding of the phenomenon being modeled and consists of many stages. A thorough analysis of the examined problem allows for the creation of a theoretical model, which is then implemented in the form of a computer program. Moreover, the results obtained during simulation using a computer program must be verified and validated.

Model verification involves checking its compliance computer implementation with assumptions expressed in the form of a conceptual model (Tucker, 2014), while validation ensures that both conceptual models and computer models are an appropriate representation of the theory or phenomenon under study (David, 2013).

In the case of social simulation, the verification methods include:

- dynamic methods that rely on checking the computer program through various ranges of input parameters,
- static methods that mainly focus on the detection of program code errors and are aimed at showing that the computer model adequately performs its tasks without software flaws.

In the case of validation, it is important whether the goal of the model is prediction or explanation. The purpose of social simulations is mainly to explain modeled phenomena. In this case, validation consists in demonstrating that the mechanisms created in the model through simulation are able to reproduce behavior similar to real ones, i.e. assess whether the structure of mechanisms at the micro level allows for the creation of effects at the macro level consistent with known theories or real data

It should be noted that, unlike mathematical models, descriptions of simulation models are often chaotic and incomplete. As a result, replication of the achieved results is difficult or impossible. Therefore, in addition to the usual description of the model, it can also be described according to the ODD protocol (i.e. The Overview, Design concepts and Details). The ODD protocol is a set of rules that standardize the description of an agent model, ensuring that this description is consistent, logical and complete (Grimm et al., 2022).

The ODD protocol consists of seven parts, sequentially presenting the most important aspects of the ABM (Grimm et al., 2010, 2022):

- *Purpose and patterns*, devoted to presenting the purpose of building the model and planned evaluation methods.
- *Entities, state variables and scales*, devoted to the modeled agents and global variables governing the course of the simulation.
- *Process overview and scheduling*, devoted to the processes that units in the model are subject to, with particular emphasis on the order in which these processes occur.
- *Design concept*, devoted to eleven key aspects building a ABM.
- *Initialization*, devoted to the mechanism of initialization of the simulation model.
- *Input data*, dedicated to those used for parameterization given model.
- *Submodels*, dedicated to component models that are part of the main model.

4. Conclusion

An organization is a multidimensional, multi-aspect and complex system, especially an organization considered in the context of a social system. There are many emergent phenomena in such a system. Undoubtedly, this state of affairs is an impulse to look for specific tools to analyze and describe the processes taking place in the organization. A new direction is analysis within the theory of complex adaptive systems, which aim to model and explain the behavior of systems of interconnected objects based on knowledge of the laws of individual elements (at the local level) and the structure (network) of their connections. Therefore, the use of computer tools developed based on complexity theory, especially agent-based models, seems interesting. This approach is postulated by Lichtenstein and McKelvey (2011) after an in-depth analysis of emergent phenomena in organization and management. Moreover, as Seel (2000) points out, change in an organization used to focus on "change planning"; it is now seen rather as “facilitating emergence.”

The complex phenomenon of emergence offers insight into issues that are increasingly important to management researchers and increasingly relevant to the leaders of our 21st century organizations.

Acknowledgements

This paper was published as part of the statutory research ROZ 1: BK-274/ROZ1/2023 (13/010/BK_23/0072) at the Silesian University of Technology, Faculty of Organization and Management.

References

1. Anderson, P. (1999). Complexity Theory and Organization Science. *Organization Science, 10(3),* 216-232.
2. Artime, O., De Domenico, M. (2022). From the origin of life to pandemics: emergent phenomena in complex systems. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 380(2227),* 1-21.
3. Axelrod, R. Cohen, M.D. (2000). *Harnessing Complexity: Organisational Implications of a Scientific Frontier.* Free Press.

4. Axelrod, R. (1997). *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration.* New York: Princeton Univercity Press.
5. Axelrod, R., Mitchell, W., Thomas, R., Bennett, D., Bruderer, E. (1995). Coalition formation in standard-setting alliances. *Management Science, 41*, 1493-1508.
6. Bohórquez Arévalo, L.E., Espinosa, A. (2015). Theoretical approaches to managing complexity in organizations: A comparative analysis. *Estudios Gerenciales, 31*, 20-29.
7. Bonabeau, E., Dorigo, M., Theraulaz, G. (1999). *Swarm Intelligence*. Oxford University Press.
8. Borgatti, S.P., Mehra, A., Brass, D.J., Labianca, G. (2009). Network Analysis in the Social Sciences. *Science, 323,* 892-895.
9. Burkhart, R. (1996). *The SWARM simulator: Applications in science and business. Embracing Complexity: Exploring the Application of Complex Adaptive Systems to Business.* Cambridge MA: Ernst & Young Center for Business Innovation.
10. Burt, R.S. (1992). *Structural Holes: The Social Structure of Competition*. Cambridge, MA: Harvard University Press.
11. Carley, K.M. (1999). Learning within and among organizations. *Advances in Strategic Management, 16,* 33-53.
12. Checkland, P. (1981). *Systems thinking, systems practice*. John Wiley & Sons Ltd.
13. Contractor, N.S., Whitbred, R., Fonti, F., Hyatt, A., O'Keefe, B., Jones, P. (2000). *Structuration theory and self-organizing networks*. Paper presented at the Annual Organization Science Winter Conference, January, Keystone, CO.
14. Crowston, K. (1996). An approach to evolving novel organizational forms. *Computational and Mathematical Organization Theory, 2(1),* 29-47.
15. David, N. (2013). Validating Simulations. In: B. Edmonds, R. Meyer (eds.), *Simulating Social Complexity*. Berlin/Heidelberg: Springer-Verlag.
16. Edmondson, D.L., Kern, F., Rogge, K.S. (2019). The co-evolution of policy mixes and socio-technical systems: towards a conceptual framework of policy mix feedback in sustainability transitions. *Res. Policy, 48*, 103555.
17. Fleming, L., Sorenson, O. (2001). Technology as a complex adaptive system. *Research Policy, 30(7),* 1019-1039.
18. Ganco, M., Agarwal, R. (2009). Performance differentials between diversifying entrants and entrepreneurial start-ups: a complexity approach. *Academy of Management Review, 34(2),* 228-252.
19. Goldstein, J. (1999). Emergence as a construct: History and issues. *Emergence, 1(1),* 49-72.
20. Gotts, N.M., Polhill, J.G., Law, A.N.R. (2003). Agent-Based Simulation in the Study of Social Dilemmas. *Artificial Intelligence Review, 19,* 3-92.
21. Granovetter, M. (1978). Threshold models of collective behavior. *American Journal of Sociology, 83(6),* 1420-1443.

22. Grimm, V., Berger, U., DeAngelis, D.L., Polhill, J.G., Giske, J., Railsback, S.F. (2010). The ODD protocol: A review and first update. *Ecological Modelling, 221(23),* 2760-2768.
23. Grimm, V., Railsback, S.F., Vincenot, C.E., Berger, U., Gallagher, C., DeAngelis, D.L., Edmonds, B., Ge, J., Giske, J., Groeneveld, J., Johnston, A.S., Milles, A., Nabe-Nielsen, J., Polhill, J.G., Radchuk, V., Rohwäder, M.-S., Stillman, R.A., Thiele, J.C., Ayllón, D. (2020). The ODD Protocol for Describing Agent-Based and Other Simulation Models: A Second Update to Improve Clarity, Replication, and Structural Realism. *Journal of Artificial Societies and Social Simulation, 23(2),* 7-27.
24. Gunz, H., Lichtenstein, B.B., Long, R. (2001). Self-organization in career systems: a view from complexity science. *M@n@gement, 5(1),* 63-88.
25. Kauffman, S. (2000). *Investigations*. Oxford University Press
26. Kowalska-Styczeń, A., Sznajd-Weron, K. (2012). Access to information in word of mouth marketing within a cellular automata model. *Advances in Complex Systems, 15(7),* 1250080.
27. Krugman, P. (1996). *The Self-Organizing Economy.* Oxford, UK: Blackwell.
28. LeBaron, B. (2000). Empirical regularities from interacting long- and short-memory investors in an agent-based stock market. *IEEE Transaction on Evolutionary Computation, 5(5),* 442-455.
29. Lichtenstein, B.B, Mckelvey, B. (2011). Four types of emergence: A typology of complexity and its implications for a science of management. *International Journal of Complexity in Leadership and Management, 1(4),* 339-378.
30. Lichtenstein, B.B, Plowman, D.A. (2009). The leadership of emergence: A complex systems leadership theory of emergence at successive organizational levels. *The Leadership Quarterly, 20(4),* 617-630.
31. Macy, M.W. (1991). Threshold effects in collective action. *American Sociological Review, 56(6),* 730-747.
32. Maguire, S., McKelvey, B. (1999). Complexity and management: Moving from fad to firm foundations. *Emergence, 1(2),* 19-61.
33. Mainzer, K. (1994). *Thinking in Complexity: The Complex Dynamics of Matter, Mind, and Mankind.* New York: Springer.
34. McKelvey, B., Salmador Sanchez, M.P. (2011). *Explaining the 2007 bank liquidity crisis: lessons from complexity science and econophysics. Working paper*. Facultad de Ciencias Económicas, Universidad Autónoma de Madrid.
35. Meyer, A.D., Gaba, V., Colwell, A. (2005). Organizing Far from Equilibrium: Nonlinear Change in Organizational Fields. *Organization Science, 16(5),* 456-473.
36. Miller, J.H., Page, S.E. (2007). *Complex Adaptive Systems.* Princeton University Press.
37. Mitleton-Kelly, E. (2003). Ten Principles of Complexity & Enabling Infrastructures. In: E. Mitleton-Kelly (ed.), *Complex Systems & Evolutionary Perspectives of Organisations: The Application of Complexity Theory to Organisations*. London: Elsevier.

38. Newman, D. (1996). Emergence and strange attractor. *Philosophy of Science, 63(2),* pp. 245-261.
39. Nonaka, I. (1994). A dynamic theory of organizational knowledge creation. *Organization Science, 5(1),* 14-37.
40. Paul, D.L., Butler, J.C., Pearlson, K.E., Whinston, A.B. (1996). Computationally modeling organizational learning and adaptability as resource allocation: an artificial adaptive systems approach. *Computational and Mathematical Organization Theory, 2(4),* 301-324.
41. Plowman, D.A., Baker, L., Beck, T., Silansky, S., Kulkarni, M., Travis, D. (2007). Radical change accidentally: The emergence and amplification of small change. *Academy of Management Journal, 50,* 515-543.
42. Plsek, P., Greenhalgh, T. (2001). The challenge of complexity in health care. *British Medical Journal, 323,* 625-628.
43. Porter, M., Siggelkow, N. (2008). Contextual interactions within activity systems and sustainability of competitive advantage. *Academy of Management Perspectives, 22(2),* 34-56.
44. Quitzow, R. (2015). Dynamics of a policy-driven market: the co-evolution of technological innovation systems for solar photovoltaics in China and Germany. *Environ. Innov. Soc. Transit., 17,* 126-148.
45. Rammela, Ch., Stagl, S., Wilfing, H. (2007). Managing complex adaptive systems — a co-evolutionary perspective on natural resource management. *Ecological Economics, 63,* 9-21.
46. Rotmans, J., Loorbach, D. (2009). Complexity and Transition Management. *Journal of Industrial Ecology, 13(2),* 184-196.
47. Sanders, T.I., McCabe, J.A. (2003). *The Use of Complexity Science*, http://www.hcs.ucla.edu/DoEreport.pdf.
48. Schelling, T. (1978). *Micromotives and Macrobehavior.* New York: W.W. Norton.
49. Seel, R. (2000). Culture and Complexity. New Insights on Organizational Change. *Organizations & People, 7(2),* 2-9.
50. Thomas, C., Kaminska-Labbé, R., McKelvey, B. (2005). Managing the MNC and exploitation/exploration dilemma: from static balance to irregular oscillation. In: G. Szulanski, Y. Doz, J. Porac (Eds.), *Advances in Strategic Management, 22*, 213-247. Oxford, UK: Elsevier.
51. Tucker, C.E. (2014). Social networks, personalized advertising, and privacy controls. *Journal of Marketing Research, 51(5),* 546-562.