Nonlinear Dynamics, Psychology, and Life Sciences, Vol. 22, No. 1, pp. 1-13.

Advanced Modeling Methods for Studying Individual Differences and Dynamics in Organizations: Introduction to the Special Issue

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A new scientific paradigm has been evolving for some time now and gradually acquiring more consensus in such fields as strategic management and organizational studies. It is typified by the concept of an organization as a *complex adaptive system* (Anderson, 1999; Dooley, 1997). In an early contribution to the field, Herbert Simon (1962) defined a complex system as being made up of a large number of interacting parts that produce hierarchical structures that are not readily decomposed into its contributing parts (Rosser & Rosser, 2015). Following this definition, it becomes possible to apply the label *complex system* to most of the organizations we know with the human aspects that characterize them. For example, business organizations, which are composed of such *factors* as employees, instruments, tools and devices, and *processes* such as decision-making (Arrow, McGrath, & Berdahl, 2000; Ceschi, Demerouti, Sartori, & Weller, 2017; Sartori & Ceschi, 2011; Weller, Ceschi, & Randolph, 2015), undoubtedly represent complex systems (Sterman, 2000). The factors and processes self-organize into a coherent and coordinated work system, or at least they *should* do so.

Importantly, systems also adapt. They assemble a structure to meet certain needs, one of which is to reduce the amount of energy required to carry out their functions, and to do so they reduce their internal level of complexity needed to respond to environmental demands. This is the *minimum entropy principle* that can be observed in physiological and individual cognitive processes also (Guastello et al., 2014; Hong, 2010). The systems have the means (sensors) for maintaining environmental awareness, making sense of incoming information, which might have a complex nature in its own right (Baber & McMaster, 2016; Weick, 2005), and formulating and taking action. Furthermore, the internal processes can reorganize to meet with new demands. To do so, the organization must maintain a sufficient level of internal complexity to make the required range of adaptive responses to the environment. This combination of reducing entropy and maintaining complexity results in an *optimal level of complexity*, which can be observed at the system levels of biology, individual psychology, teams, and organizations (Navarro & Rueff-Lopes, 2015; Schuldberg, 2015).

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Complexity can also be observed in a time series analysis of events. Here one can utilize entropy statistics, fractal dimensions, Lyapunov exponents, and other techniques to detect specific nonlinear dynamics – attractors of different sorts, bifurcations, chaos, and their overall level of volatility of movement.

The standard methods of investigation applied in organizational psychology, which are usually based on linear correlation coefficients (including structural equation modeling, SEM), do not always guarantee the possibility of analyzing and predicting outcomes of the macroscopic structure or the emergent properties of complex systems such as business organizations; see for example Ceschi, Hysenbelli, Sartori, and Tacconi, (2014), Ceschi, Scalco, Dickert, and Sartori, (2015), Ceschi, Dorofeeva, Sartori, Dickert, and Scalco, (2015), Scalco, Ceschi, Shiboub et al., (2017). In addition, traditional statistical analysis methods do not always consider the full effect of individual differences of the population (Murphy, 1996).

New research techniques, based on recent developments in computer science and advanced statistical analyses, have arisen during the last two decades that afford these possibilities. Starting from some solid scientific studies on individual behavior and using advanced computing techniques capable of "growing up" phenomena at a macro level, it becomes possible to obtain counterintuitive findings about behavior and implications in organizations (Farmer & Foley, 2009). *Computational social science* (CSS) is the investigation of social phenomena and organizations on many scales, ranging from individual actors to the largest groupings through the medium of computation (Cioffi-Revilla, 2014). Methods classified within CSS include social network analysis, agent-based modeling (ABM), complexity modeling, and social simulation models. Each of the foregoing techniques comes with several specializations that have been productive for studying organizational (Carley & Prietula, 1994; Dal Forno & Merlone, 2004; Frantz & Carley, 2009; Kalish, 2013; Lomi & Larsen, 2001; Phelan, 2004) and other social phenomena (Buchanan, 2002; Elliott & Kiel, 2004; Nowak, Gelfand, Barkowski, Cohen, & Hernandez, 2016; Smith & Conrey, 2007; Vallacher, Read, & Nowak, 2017).

The present special issue proposes new approaches for organizational studies, a hybrid between the classical statistical model approach, and the dynamic modeling. These methods are not presented as substitutes for the traditional statistical analyses, but as extensions of it, in order to obtain results capable of explaining as much variance as possible in the situations analyzed. Thus one aim of this special issue is to develop a new approach that allows a direct comparison of ABM and GMM results with standard and SEM-based statistical methodologies, whilst retaining the potential advantages of these new methods. The special issue focuses on methodology and instruments by proposing examples and applications of the methods proposed.

A second objective of this special issue is to find new ways for exploring nonlinear dynamics in organizations, with special attention to emergent processes. Oddly, organizational behavior was one of the first areas of psychology to adopt the nonlinear paradigm (neuroscience being another; Guastello, 2009a). Its nonlinear theories outpaced empirical studies by a wide margin (Dooley, 2009), even though there were some notable exceptions to this trend. For this reason *NDPLS* published a special issue that featured developments in substantive organizational theory that displayed principles of nonlinear dynamics (Backström, Hagström, & Göransson, 2013; de Cabo & Gimeno, 2013; Dooley, Kiel, & Dietz, 2013; Frantz & Carley, 2013; Guastello et al., 2013; Navarro, Curioso, Gomes, Arrieta, & Cortés, 2013; Pathak, Pokharel, & Mahadevan, 2013; Salem, 2013; Stevens, Gorman, Amazeen, Likens, & Galloway, 2013).

SYSTEM DYNAMICS AND AGENT-BASED MODELING (ABM)

System dynamics (Forrester, 1961) represent the earliest kind of simulation models inside CSS. This method has been quite popular in organizational science and economics departments during the last decades, thanks to the fact that it is a useful technique, for instance, for describing and forecasting economic processes (Gilbert, 2008). However, organizational psychology research could not benefit from it, given the fact that system dynamic models follow a strong deterministic approach based on structural equation models, the veracity of which could be quite wrong (Rosser, 1999). Moreover, system dynamics works only by taking into account populations (or aggregated variables more generally), instead of single agents. ABM overcomes this gap: “ABM is essentially the application of autonomous agents programmed to behave in different ways when interacting with adjacent agents or different aspects of their environment on a dimensional grid … [ABM] examines ‘emergent’ behavior as a structure and pattern that develops from numerous micro-level interactions” (Elliott & Kiel, 2004, p. 121-122). An example output from an ABM analysis of a social network appears in Fig. 1.

As stated by Gilbert (2008), contrary to most other types of mathematical models, ABMs are able to work with heterogeneous agents in their characteristics and abilities. In fact, within an ABM, it is possible to create several agents (from 2 to even thousands, depending on the computational resources available) and to model multiple characteristics of agents within an indefinite range, allowing the researcher to replicate the individual differences observed through experimental studies within the virtual simulation. An ABM also gives the researcher the chance to build agents that are able to influence each other, react to their experience (i.e., have memory), and independently learn from their actions.

As Liao (2011) stated, social behavior can be studied through two different approaches: The first one relies on collecting several observations, arranging data, and analyzing them; the final and anticipated outcome is represented by a model that fits such data. The second approach asks researchers to have some prior knowledge about a certain social mechanism and then build a model of it. With the latter approach, researchers can simulate dynamics, test several hypotheses and, in the end, gain a better understanding of complex social systems. Railsback and Grimm (2011) stated that real-world systems are either too complex or they evolve too slowly to be examined by means of experiments;

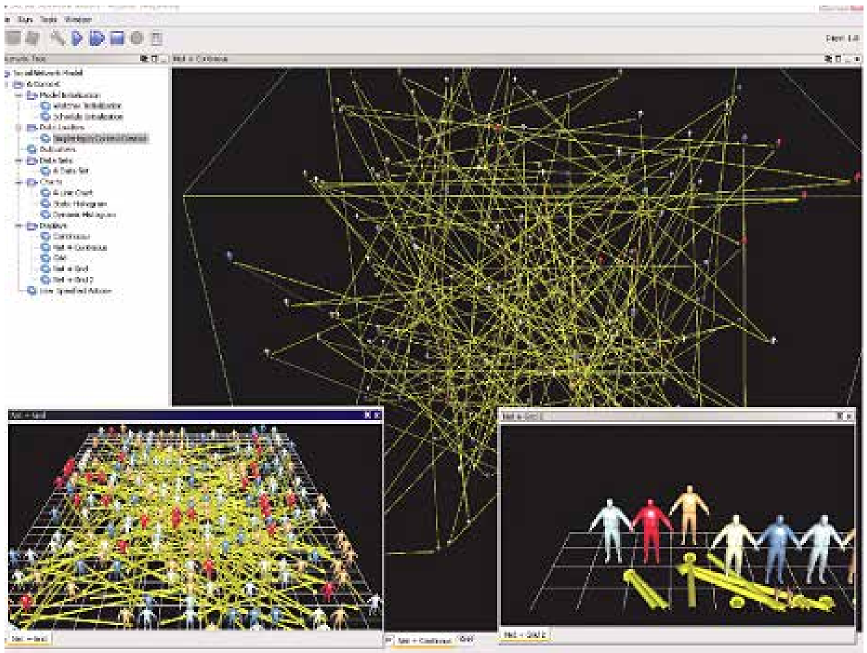

Fig. 1. Agents interacting in a self-organizing social network inside a virtual simulation of social influence. Image by Kurt Severance, NASA, and Kenneth Zick, U. Michigan (from Samuelson & Macal, 2006). In the public domain.

indeed, this situation appears to be true for most of the social processes encountered inside organizations. By means of ABM, organizational psychologists have the chance to model organizations where agents, which represent employees, have a certain role, an individual ability to communicate with others, a personal skill that impacts on the speed of execution of the work, his or her own opinions, and even a peculiar ability to manage emotions (Deloach, Oyenan, & Matson, 2008). Thus, as described, ABM offers new unique opportunities for research in organizational psychology. As Cioffi-Revilla (2010) suggested, as the microscope has granted to physics the access to an incredible micro-universe made up of earlier unnoticed elements, laws, and processes, computational simulations are the instrument that can drive new theories and applications by means of unprecedented replication and virtual experimentation of social and organizational process.

LATENT CLASS GROWTH ANALYSIS (LCGA) AND GROWTH MIXTURE MODELING (GMM)

In parallel to the development of simulation techniques for organizational phenomena, the structural equations modelling (SEM) community has developed new methods, such as the latent class growth analysis (LCGA) and growth mixture modeling (GMM), both of which allow modeling individual differences and recognising homogeneous groups within a larger heterogeneous population. Although the SEM-based models developed from the linear-based model of problem framing and data analysis, they are starting to acquire more affinity with nonlinear dynamics. For instance, growth curve modelling evolved from a framework where a variable X is a function of time to one in which X at time-2 is a function of X at time-1 (Ployhart & Kim, 2013). Although this transition seems simple, the treatment of time as an implicit variable, rather than an explicit variable, is a hallmark of nonlinear dynamical processes.

Micro-heterogeneity is re-established into the analysis with the ABMs and the GMMs. The ABM approach additionally allows experimentation with parameters such as individual's rationality, something that is difficult to address with a purely statistical approach (Richetin et al., 2010). Indeed, a promising area of application of the ABMs and the GMMs is organizational behavior, where it is possible to model social behaviors to investigate organizational outcomes (Smith & Conrey, 2007). Knowing, for example, the potential antecedents connected to some social behaviors, such as counterproductive behaviors (interpersonal deviance, abusive supervision, etc.), as well as behaviors oriented to positive psychology (such as teamwork, career choices, etc.), makes it possible to recreate the same phenomena by using computer simulation for predictive purposes (Ceschi, Sartori, Tacconi & Hysenbelli, 2014; Ceschi, Rubaltelli, & Sartori, 2014; Fioretti, 2013; Hughes, Clegg, Robinson, & Crowder, 2012; Sartori & Ceschi, 2013; Sartori, Ceschi, & Costantini, 2015; Sartori, Ceschi, & Scalco, 2014; Scalco, Ceschi, & Sartori, 2017; Scalco, Ceschi, Sartori, & Rubaltelli, 2015; Weinhardt & Vancouver, 2012).

In the usual growth modeling approach, a single growth trajectory is estimated, and the non-obvious situation that individuals come from a single population is assumed. Another too strict assumption concerns that predictors and covariates affect each individual in like manner. We know that subgroups can be commonly identified within a population (e.g., in organizational psychology, departments, work-teams, companies), so that it should be actually misleading not to properly consider this source of complexity. To avoid this oversimplification, a latent class growth analysis (LCGA) or growth mixture (GMM) modelling approach allows the researcher to capture the complex growth patterns that define changes among members of different groups. GMM allows for differences in growth parameters across unobserved sub-populations. To achieve this aim, latent trajectory classes are used, allowing for different groups of individual growth trajectories to vary around different means or asymptotes. The results are separate growth models for each latent class, each with its unique estimates of variances and covariate influences (Muthén & Asparaouhov, 2006; Wang & Zhou, 2013). LCGA is a particular kind of GMM, with the assumption that variance and covariance estimates for the growth factors within each class are null. By this assumption, all individual growth trajectories within a class are homogeneous. In this way, it is possible to identify distinct groups in a first step, before conducting

GMM. This approach has been deeply studied by Nagin and Land (1993) and Muthén and colleagues (Muthén & Asparaouhov, 2006; Nylun, Asparouhov, & Muthén, 2007).

DYNAMIC AND "GROWING UP" MODELS

Another approach that can be considered for studying complexity is the *generative approach*, where methods help to generate events and hypotheses that would be impossible to recreate or observe in real life (Sloman & Sloman, 1978). Indeed, computer simulation has become an essential tool to generate observable facts. These advanced analytic analyses allow an alternative way of modeling and understanding dynamic social processes (Epstein, 2009; Epstein & Axtell, 1996; Lomi & Larsen, 2001). The chance to explore emergent phenomena has been recently taken into account and revisited. As already said, starting from some solid scientific studies on individual behavior and using advanced computing techniques such as ABM, which are capable of "growing up" phenomena at the macro level, it is possible to obtain predictive findings about human behavior in relation with the organizations studied (Farmer & Foley, 2009). Similarly, LCGA and GMM can capture the complex growth patterns that define changes over time with different growth parameters across unobserved sub-populations (Nagin & Land, 1993).

THE CONTRIBUTIONS TO THIS ISSUE

The first four articles in this issue employ the methodology combination of ABM, LCGM, and GMM. Scalco, Ceschi, and Sartori (2018) explain how a psychological theory can be framed as a problem that could be solved using the capabilities of ABM. The theory of planned behaviour is a well-known theory of attitude-behavior relationships, which are in turn historically important in organizational psychology.

Burro, Raccanello, Pasini, and Brondino (2018) used LCGA to identify clusters of reactions to a terrorist attack based on positive and negative affect and personality traits. The nature and relative size of the clusters should be helpful to emergency response units that need to organize, plan, and deliver a post-crisis intervention.

Alessandri, Perinelli, De Longis, and Theodorou (2018) carefully explained the analytic and heuristic steps they used to extract job performance curves using GMM. They did not test a catastrophe model in its literal form (other methods exist for that purpose), but rather they used it as theoretical guidance for explaining why performance growth curves should be expected and how they could be interpreted. It also follows that particular trends in growth curve parameters might suggest that a catastrophe process could be involved. Cusp catastrophes happen to be synonymous mathematically with phase shifts (Gilmore, 1981), and they are one of a few distinct dynamics that could underlie self-organizing processes (Goldstein, 2011; Guastello, 2005).

It is a well-known problem in group dynamics that, on one hand, homogenous groups can be more cohesive and productive for some types of tasks, but not when creative problem solving is involved. Heterogeneous groups perform better at creative problem solving, but are prone to greater conflict (Zander, 1994). In the fourth article, Estevez-Mujica, Acero, Jimenez-Leal and Garcia-Diaz (2018) studied the connection between homophilic clustering within problem solving groups and how the clusters impact on performance. Further analysis with ABM based on the experimental data produced new insights into the group dynamics beyond what was evident in data treated in the conventional fashion.

Moving forward into more new methods for organizational dynamics, Rueff-Lopes, Navarro, and Silva (2018) used an artificial neural network to connect positive and negative emotions to an individuals' propensity to communicate their opinions through a social network. Negative affect spread faster than positive affect. Word of mouth dynamics are a form of emotional contagion that is thought to underlie the well-known S-curve for product adoption (Rogers, 1962). It has already been shown that the S-curves can be represented in greater detail as nonlinear dynamical processes (Jacobsen & Guastello, 2011), and also appear to be amenable to GMMs.

Another connection worth reflecting upon is the merit of measuring positive and negative attitudes or emotions separately and using them as separate variables when studying nonlinear dynamics. Approach and avoidance gradients in basic motivation have been known since Brown (1948). They were first incorporated as gradients in catastrophe manifolds in models for work motivation and conflict (Guastello, 1981, 1987, 2009b), and more recently achievement motivation in educational settings (Stamovlasis & Gorida, in press; Stamovlasis & Sideridis, 2014), and mood regulation in clinical contexts (Kuhl, Mitina, & Koole, 2017). Different dynamics could be involved, depending how one frames the problem.

Warren's (2018) study of stakeholders in an educational system offers another new way to explore self-organizing phenomena. Given that self-organization is a fundamentally nonlinear process, the present of polynomial functions in a static analysis suggests that a generalizable dynamic model could be viable. Future research would need to determine how similar Warren's research setting is similar to other localized settings in order to extrapolate broader global dynamics.

In the grand finale for this issue, Kern, Karwowski, Gutierrez, and Murata (2018) tackle a problem that has been haunting vigilance researchers for decades. Hancock (2013) observed that performance in laboratory studies of vigilance drops markedly after as little as 20 minutes on task, but performance in real-world vigilance tasks can sustain for many hours without a decrement. Differences in the motivational structures of the research settings and the artificial nature of the laboratory apparatus were the top two explanations for such differences. Kern et al.'s analysis of vigilance performance in real-world settings showed that performance trends were actually chaotic, and apparently another example of the chaotic variability in performance that Navarro et al. (2013) reported as natural occurrences for other tasks.

Chaos, catastrophes, ABMs, and neural networks are not strangers to the nonlinear dynamics community, and we hope their benefits to the broader scope of organizational theory and research will be apparent soon. GMM and LCGA are newcomers to the toolkit of nonlinear methods, and offer unique advantages for exploring nonlinear dynamical systems.

REFERENCES

Alessandri, G., Perinelli, E., De Longis, E., & Theodorou, A. (2018). Second order growth mixture modeling in organizational psychology: An application in the study of job Performance. *Nonlinear Dynamics, Psychology, and Life Sciences, 22,* 53-76.

Anderson, P. (1999). Complexity theory and organization science. *Organization Science, 10,* 216-232.

Arrow, H., McGrath, J. E., & Berdahl, J. L. (2000). *Small groups as complex systems*. Thousand Oaks, CA: Sage.

Baber, C., & McMaster, R. (2016). *Grasping the moment: Sensemaking in response to routine incidents and major emergencies*. Boca Raton, FL: CRC Press.

Backström, T., Hagström, T., & Göransson, S. (2013). Communication and a mechanism for cultural integration. *Nonlinear Dynamics, Psychology, and Life Sciences, 17,* 87-106.

Buchanan, M. (2002). *Nexus: Small worlds and the groundbreaking theory of networks*. New York, NY: W. W. Norton.

Brown, J. S. (1948). Gradients of approach and avoidance responses and their relation to motivation. *Journal of Comparative and Physiological Psychology, 41,* 450-465.

Burro, R., Raccanello, D., Pasini, M., & Brondino, M. (2018). An "open-source estimation" of latent class extended mixed models in R. Affect profiles after terroristic attacks. *Nonlinear Dynamics, Psychology, and Life Sciences,22, 35-52.*

Carley, K. M., & Prietula, M. J. (Eds.). (1994). *Computational organization theory*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Ceschi, A., Demerouti, E., Sartori, R., & Weller, J. (2017). Decision-making processes in the workplace: How exhaustion, lack of resources and job demands impair them and affect performance. *Frontiers in Psychology, 8,* 313.

Ceschi, A., Dorofeeva, K., Sartori, R., Dickert, S., & Scalco, A. (2015). A simulation of householders' recycling attitudes based on the theory of planned behavior. In J. Bajo, J. Z., Hernández, P. Mathieu, A. Campbell, A. Fernández-Caballero, M. N. Moreno, V. Julián, A. Alonso-Betanzos, M. D. Jiménez-López, & V. Botti. (Eds.), *Trends in practical applications of agents, multi-agent systems and sustainability* (pp. 177-184). Cham, Switzerland: Springer.

Ceschi, A., Hysenbelli, D., Sartori, R., & Tacconi, G. (2014). Cooperate or defect? How an agent based model simulation on helping behavior can be an educational tool. In T. D. Mascio, R. Gennari, P. Vittorini, R. Vicari, R., & F. Prieta (Eds.), *Methodologies and intelligent systems for technology enhanced learning* (pp. 189-196). Cham, Switzerland: Springer.

Ceschi, A., Rubaltelli, E., & Sartori, R. (2014). Designing a homo psychologicus more psychologicus: empirical results on value perception in support to a new theoretical organizational-economic agent based model. In S. Omatu, H. Bersini, J. M. Corchado, S. Rodríguez, P. Pawlewski, & E. Bucciarelli, E. (Eds.), *Distributed computing and artificial intelligence, 11th international conference* (pp. 71-78). Cham, Switzerland: Springer.

Ceschi, A., Sartori, R., Tacconi, G., & Hysenbelli, D. (2014). Business games and simulations: which factors play key roles in learning. In T. D. Mascio, R. Gennari, P. Vittorini, R. Vicari, R., & F. Prieta (Eds.), *Methodologies and intelligent systems for technology enhanced learning* (pp. 181-187). Cham, Switzerland: Springer.

Ceschi, A., Scalco, A., Dickert, S., & Sartori, R. (2015). Compassion and prosocial behavior: Is it possible to simulate them virtually? In J. Bajo, J. Z., Hernández, P. Mathieu, A. Campbell, A. Fernández-Caballero, M. N. Moreno, V. Julián, A. Alonso-Betanzos, M. D. Jiménez-López, & V. Botti. (Eds.), *Trends in practical applications of agents, multi-agent systems and sustainability* (pp. 207-214). Cham, Switzerland: Springer.

Cioffi-Revilla, C. (2010). A methodology for complex social simulations. *Journal of Artificial Societies and Social Simulations, 13*(1), 7.

Cioffi-Revilla, C. (2014). *Introduction to computational social science*. Berlin: Springer.

Dal Forno, A., & Merlone, U. (2004). Personnel turnover in organizations: An agent-based simulation model. *Nonlinear Dynamics, Psychology, and Life Sciences, 8,* 205-230.

de Cabo, R. M., & Gimeno, R. (2013). Estimating population ecology models for the WWW market: Evidence of competitive oligopolies. *Nonlinear Dynamics, Psychology, and Life Sciences, 17,* 159-172.

Deloach, S. A., Oyenan, W. H., & Matson, E. T. (2008). A capabilities-based model for adaptive organizations. *Autonomous Agents and Multi-Agent Systems, 16,* 13-56.

Dooley, K. J. (1997). A complex adaptive systems model of organization change. *Nonlinear Dynamics, Psychology, and Life Sciences, 1*, 69-97.

Dooley, K. J. (2009). Organizational psychology. In S. J. Guastello, M. Koopmans, & D. Pincus (Eds.), *Chaos and complexity in psychology: The theory of nonlinear dynamical systems* (pp. 434-451). New York: Cambridge University Press.

Dooley, K. J., Kiel, L. D., & Dietz, A. S. (2013). Introduction to the special issue on nonlinear organizational dynamics. *Nonlinear Dynamics, Psychology, and Life Sciences, 17,* 1-2.

Elliott, E., & Kiel, L. D. (2004). Agent-based modeling in the social and behavioral sciences. *Nonlinear Dynamics, Psychology, and Life Sciences, 8*, 121-130.

Epstein, J. M. (2009). Modelling to contain pandemics. *Nature, 460*, 687-687.

Epstein, J. M., & Axtell, R. (1996). *Artificial societies: Social science from the bottom up.* Cambridge, MA: MIT Press.

Estévez-Mujica, C. P., Acero, A., Jiménez-Leal, W., García-Díaz, C. (2018). The influence of homophilous interactions on diversity effects in group problem-solving. *Nonlinear Dynamics, Psychology, and Life Sciences, 22*, 77-102.

Farmer, J. D., & Foley, D. (2009). The economy needs agent-based modelling. *Nature, 460*, 685-686.

Fioretti, G. (2013). Agent-based simulation models in organization science. *Organizational Research Methods, 16*, 227-242.

Forrester, J. W. (1961). *Industrial dynamics*. Cambridge, MA: MIT Press.

Frantz, T. L., & Carley, K. M. (2009). Agent-based modeling within a dynamic network. In S. J. Guastello, M. Koopmans, & D. Pincus (Eds.), *Chaos and complexity in psychology: The theory of nonlinear dynamical systems* (pp. 475-505). New York: Cambridge University Press.

Frantz, T. L., & Carley, K. M. (2013). The effects of legacy organization culture on post-merger integration. *Nonlinear Dynamics, Psychology, and Life Sciences, 17,* 107-132.

Gilbert, N. (2008). *Agent-based models*. Thousand Oaks, CA: Sage.

Gilmore, R. (1981). *Catastrophe theory for scientists and engineers*. New York, NY: Wiley.

Goldstein, J. (2011). Emergence in complex systems. In P. Allen, S. Maguire , & B. McKelvey (Eds.), *The Sage handbook of complexity and management* (pp. 65–78). Thousand Oaks, CA: Sage.

Guastello, S.J. (1981). Catastrophe modeling of equity in organizations. *Behavioral Science, 26,* 63-74.

Guastello, S.J. (1987). A butterfly catastrophe model of motivation in organizations: Academic Performance. *Journal of Applied Psychology, 72,* 165-182.

Guastello, S. J. (2005). Statistical distributions and self-organizing phenomena: What conclusions should be drawn? *Nonlinear Dynamics, Psychology, and Life Sciences, 9*, 463-478.

Guastello, S. J. (2009a). Chaos as a psychological construct: Historical roots, principal findings, and current growth directions. *Nonlinear Dynamics, Psychology, and Life Sciences, 13*, 289-310.

Guastello, S. J. (2009b). Chaos and conflict: Recognizing patterns. *Emergence: Complexity in Organizations, 10*(4), 1-9.

Guastello, S. J., Boeh, H., Gorin, H., Huschen, S., Peters, N. E., Fabisch, M., & Poston, K. (2013). Cusp catastrophe models for cognitive workload and fatigue: A comparison of seven task types. *Nonlinear Dynamics, Psychology, and Life Sciences, 17*, 23-48.

Guastello, S. J., Reiter, K., Shircel, A., Timm, P., Malon, M., & Fabisch, M. (2014). The performance-variability paradox, financial decision making, and the curious case of negative Hurst exponents. *Nonlinear Dynamics, Psychology, and Life Sciences, 14*, 297-328.

Hancock, P. A. (2013). In search of vigilance: The problem of iatrogenically created psychological phenomena. *American Psychologist, 68,* 97-109.

Hong, S. L. (2010). The entropy conservation principle: Applications in ergonomics and human factors. *Nonlinear Dynamics, Psychology, and Life Sciences, 14,* 291-315.

Hughes, H. P., Clegg, C. W., Robinson, M. A., & Crowder, R. M. (2012). Agent-based modelling and simulation: The potential contribution to organizational psychology. *Journal of Occupational and Organizational Psychology, 85*, 487-502.

Jacobsen, J. J., & Guastello, S. J. (2011). Diffusion models for innovation: S-curves, networks, power laws, catastrophes, and entropy. *Nonlinear Dynamics, Psychology, and Life Sciences, 15*, 307-333.

Kalish, Y. (2013). Harnessing the power of social network analysis to explain organizational phenomena. In J. M. Cortina & R. S. Landis (Eds.), *Modern research methods for the study of behavior in organizations* (pp. 99-135). New York, NY: Routledge.

Kern, D., Karwowski,W., Gutierrez, E., & Murata A. (2018). Evidence of chaos in a routine watchstanding task. *Nonlinear Dynamics, Psychology, and Life Sciences, 22,* 153-171.

Kuhl, J., Mitina, O., & Koole, S. L. (2017). The extended trust hypothesis: Single-attractor self-contagion in day-to-day changes in implicit positive affect predicts action-oriented coping and psychological symptoms. *Nonlinear Dynamics, Psychology, and Life Sciences, 21*,505-518.

Liao, T. F. (2011). *Statistical group comparison*. Hoboken, NJ: Wiley.

Lomi, A., & Larsen, E. R. (2001). *Dynamics of organizations: Computational modeling and organization theories*. Cambridge, MA: MIT Press.

Murphy, K. R. (1996). *Individual differences and behavior in organizations*. San Francisco, CA: Jossey-Bass.

Muthén, B., & Asparouhov, T. (2006). Item response mixture modeling: Application to tobacco dependence criteria. *Addictive Behaviors, 31*, 1050-1066.

Nagin, D. S., & Land, K. C. (1993). Age, criminal careers, and population heterogeneity: Specification and estimation of a nonparametric, mixed Poisson model. *Criminology, 31*, 327-362.

Navarro, J., Curioso, F., Gomes, D., Arrieta, C., & Cortés, M. (2013). Fluctuations in work motivation: Tasks do not matter! *Nonlinear Dynamics, Psychology, and Life Sciences, 17,* 3-22.

Navarro, J., & Rueff-Lopes, R. (2015). Healthy variability in organizational behavior: Empirical evidence and new steps for future research. *Nonlinear Dynamics, Psychology, and Life Sciences, 19,* 529-552.

Nowak, A., Gelfand, M. J., Borkowski, W., Cohen, D., & Hernandez, I. (2016). The evolutionary basis of honor cultures. *Psychological Science, 27*, 12-24.

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling, 14*, 535-569.

Pathak, S., Pokharel, M. P., & Mahadevan, S. (2013). Hypercompetition, collusion, free riding or coopetition: Basins of attraction when firms simultaneously compete and cooperate. *Nonlinear Dynamics, Psychology, and Life Sciences, 17,* 133-158.

Phelan, S. E. (2004). Using agent-based simulation to examine the robustness of up-or-out promotion systems in universities. *Nonlinear Dynamics, Psychology, and Life Sciences, 8,* 177-204.

Ployhart, R. E., & Kim, Y. (2013). Dynamic longitudinal growth modeling. In J. M. Cortina & R. S. Landis (Eds.), *Modern research methods for the study of behavior in organizations* (pp. 63-98). New York, NY: Routledge.

Railsback, S. F., & Grimm, V. (2011). *Agent-based and individual-based modeling: a practical introduction*. Princeton University Press.

Richetin, J., Sengupta, A., Perugini, M., Adjali, I., Hurling, R., Greetham, D., & Spence, M. (2010). A micro-level simulation for the prediction of intention and behavior. *Cognitive Systems Research, 11*, 181-193.

Rogers, E. M. (1962). *Diffusion of innovations*. New York, NY: Free Press.

Rosser, J. B. Jr. (1999). On the complexities of complex economic dynamics. *Journal of Economic Perspectives, 13,* 169-192.

Rosser, J. B. Jr. (1999). On the complexities of complex economic dynamics. *Journal of Economic Perspectives, 13*(4), 169-192.

Rosser, J. B. Jr., & Rosser, M. V. (2015). Complexity and behavioral economics. *Nonlinear Dynamics, Psychology, and Life Sciences, 19,* 201-226.

Rueff-Lopes, R., Navarro, J., & Silva, A. J. (2018). Emotions as proximal causes of word of mouth: A nonlinear approach. *Nonlinear Dynamics, Psychology, and Life Sciences, 22,* 103-125.

Salem, P. (2013). The complexity of organizational change: Describing communication during organizational turbulence. *Nonlinear Dynamics, Psychology, and Life Sciences, 17, 49-66.*

Samuelson, D. A., & Macal, C. M. (2006, August). Agent-based simulation comes of age: Software opens up many new areas of application. *OR/MS Today*. Retrieved November 5, 2017 from http://www.orms-today.org/orms-8-06/fragent.html

Sartori, R., & Ceschi, A. (2011). Uncertainty and its perception: Experimental study of the numeric expression of uncertainty in two decisional contexts. *Quality & Quantity*, *45*, 187-198.

Sartori, R., & Ceschi, A. (2013). Assessment and development centers: judgment biases and risks of using idiographic and nomothetic approaches to collecting information on people to be evaluated and trained in organizations. *Quality & Quantity*, *47,* 3277-3288.

Sartori, R., Ceschi, A., & Costantini, A. (2015). On decision processes in businesses, companies and organizations computed through a generative approach: The case of the agent-based modeling. *International Journal of Business Research, 15*, 25-38.

Sartori, R., Ceschi, A., & Scalco, A. (2014). Differences between entrepreneurs and managers in large organizations: An implementation of a theoretical multi-agent model on overconfidence results *Distributed computing and artificial intelligence, 11th international conference* (pp. 79-83). Berlin: Springer.

Scalco, A., Ceschi, A., & Sartori, R. (2017). The pursuit of happiness: A model of group formation. In W. Jager, R. Verbrugge, A. Flache, G de Roo, L. Hoogduin, & C. Hemelrijk (Eds.), *Advances in social simulation 2015* (pp. 367-371). Cham, Switzerland: Springer.

Scalco, A., Ceschi, A., & Sartori, R. (2018). Application of psychological theories in agent-based modeling: The case of the theory of planned behavior. *Nonlinear Dynamics, Psychology, and Life Sciences, 22,* 15-53.

Scalco, A., Ceschi, A., Sartori, R., & Rubaltelli, E. (2015). Exploring selfish versus altruistic behaviors in the ultimatum game with an agent-based model. In J. Bajo, J. Z., Hernández, P. Mathieu, A. Campbell, A. Fernández-Caballero, M. N. Moreno, V. Julián, A. Alonso-Betanzos, M. D. Jiménez-López, & V. Botti. (Eds.), *Trends in practical applications of agents, multi-agent systems and sustainability* (pp. 199-206). Cham, Switzerland: Springer.

Scalco, A., Ceschi, A., Shiboub, I., Sartori, R., Frayret, J. M., & Dickert, S. (2017). The Implementation of the theory of planned behavior in an agent-based model for waste recycling: A review and a proposal. In A. Alonso-Betanzos, A., N. Sánchez Maroño, O. Fontenla-Romero, G. J. Polhill, T. Craig, J. Bajo, & J. M. Corchado, J. M. (Eds.), *Agent-based modeling of sustainable behaviors* (pp. 77-97). Chem, Switzerland: Springer.

Schuldberg, D. (2015). What is optimum variability? *Nonlinear Dynamics, Psychology, and Life Sciences, 14,* 553-568.

Simon, H. A. (1962). The architecture of complexity. *Proceedings of the American Philsophical Society, 106*, 467-482.

Sloman, A., & Sloman, A. (1978). *The computer revolution in philosophy: Philosophy, science and models of mind* (Vol. 3). Brighton, UK: Harvester Press.

Smith, E. R., & Conrey, F. R. (2007). Agent-based modeling: A new approach for theory building in social psychology. *Personality and Social Psychology Review*, *11*, 87-104.

Stamovlasis, D., & Gonida, S.-E. N.(in press). Dynamic effects of performance avoidance goal orientation on student achievement in language and mathematics. *Nonlinear Dynamics, Psychology, and Life Sciences.*

Stamovlasis, D., & Sideridis, G. D. (2014). Ought-approach versus ought-avoidance: Nonlinear effects on arousal under achievement stiautions. *Nonlinear Dynamics, Psychology, and Life Sciences, 18, 67-90.*

Sterman, J. D. (2000). *Business dynamics: Systems thinking and modeling for a complex world*. Boston, MA: McGraw-Hill.

Stevens, R., Gorman, J. C., Amazeen, P., Likens, A., & Galloway, T. (2013). The organizational neurodynamics of teams. *Nonlinear Dynamics, Psychology, and Life Sciences, 17, 67-88.*

Vallacher, R. R., Read, S. J., & Nowak, A. (2017). Computational social psychology. New York, NY: Routledge.

Wang, M., & Zhou, L. (2013). Latent class procedures: Recent development and applications. In J. M. Cortina & R. S. Landis (Eds.), *Modern research methods for the study of behavior in organizations* (pp. 137-160). New York, NY: Routledge.

Warren, C. R. (2018). Investigating balance in teacher job attitudes using polynomial regression and response surface methodology. *Nonlinear Dynamics, Psychology, and Life Sciences*, *22,* 127-151.

Weick, K. (2005). Managing the unexpected: Complexity as distributed sensemaking. In R. R. McDaniel, Jr., & D. J. Driebe (Eds.), *Uncertainty and surprise in complex systems* (pp. 51-65). New York, NY: Springer.

Weller, J. A., Ceschi, A., & Randolph, C. (2015). Decision-making competence predicts domain-specific risk attitudes. *Frontiers in Psychology, 6*, 540.

Weinhardt, J. M., & Vancouver, J. B. (2012). Computational models and organizational psychology: Opportunities abound. *Organizational Psychology Review, 2*, 267-292.

Zander, A. (1994). *Making groups effective* (2nd edition). San Francisco, CA: Jossey-Bass.