Running Head: MEASURING COMPLEXITY

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Michael Wolf-Branigin

George Mason University

Arlington, Virginia

Complexity theory provides a promising approach in social work education as researchers and educators begin examining and quantifying the concepts of non-linearity and emergence. This paper introduces several components of complexity theory and discusses various statistical methods to consider when measuring contributions from each of these components. While social work research typically relies on group comparisons, complexity theory provides a broad framework for structuring and investigating social work phenomena. These applications include understanding how social movements emerged to viewing the interdependencies of communities.

Keywords: Social work education; Statistical methods; Complexity theory; Emergence; Non-linearity; Agent-based modeling

Michael Wolf-Branigin, Ph.D., MSW, is an Associate Professor of Social Work at George Mason University Department of Social Work. MS 1F7, 3330 Washington Blvd, Suite 150, Arlington, VA. 22201. E-mail: mwolfbra@gmu.edu. (703) 993-4229, fax (703) 993-4249.

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Is it possible be that understanding complex social service phenomena is as easy as 1) knowing your client's or organization's current functioning level, 2) identifying what attracts this client or organization to be involved in an intervention or action, 3) seeing how other clients and organizations then self organize and 4) seeing how this leads to an emergent collective behavior? To a certain extent, it is possible. By using a complexity-based approach - an established paradigm in the natural sciences – social workers can apply this promising theoretical alternative. Turner (2001) explains social work theory as the set of testable explanations based on professional activities that we perform for and with the stakeholders to whom we are accountable. This demands that we identify ways to gather homogenous data that allows us to abstract indicators of successful outcomes and tie these into differential theory outcomes.

Despite the fact that complexity has not yet achieved paradigm status within social service research as defined by Kuhn (1970), the past decade has seen an increase in scholarly articles discussing and applying complexity theory (Bolland & Atherton, 1999; Hudson, 2000; Trevillon, 2000; Hudson 2004). Recent evaluation publications have enhanced this growing interest and the related area of developmental evaluation (Williams & Imam, 2006; Westley, Zimmerman & Patton, 2006). Traditional social work research methods focus on group comparisons, whereas exploratory methods involving correlation and regression attempt to identify linear relationships. Integrating diverse research and evaluative methodologies based on linear relationships and group comparison approaches into a coherent evaluative strategy, however, requires that the methodology be sensitive to time and location.

While general systems theory equips social workers with a framework for understanding vital person-in-environment interactions, this framework poses difficulties as we quantify phenomenon over time and location. This paper provides social work educators, especially those working with advanced graduate students, an initial background on complexity theory. First, I introduce the concepts when evaluating social work phenomena in a complexity framework. Second, the paper suggests a applying a variety of statistical methods for social work researchers and educators to use when measuring the various components of complexity and emergence.

Complexity has become an accepted theoretical paradigm within the natural sciences where advanced agent-based modeling programs predict emergent behaviors (Epstein, 1999; Grimm, Revilla, Berger, Jeltsch, Mooij, Railsback, Thulke, Weiner, Weigand, & DeAngelis, 2005; Gorman, Mezik, Mezik, & Gruenewald, 2006). Its assumptions and applications, however, pose significant challenges to social service research and evaluation. In order to apply a strong quantitative complexity framework, we need to shift from a pure hypothesis testing approach to a pattern-recognition exploratory studies that identify non-linearity. As contemporary social work research and evaluation encourage the use of mixed-methods by applying both qualitative and quantitative approaches when examining the effects of social programs (Creswell, 2003), they use methods separately and therefore lack integration between the qualitative and quantitative data. The proposed framework for applying complexity to human service organizations provides a possible solution to this dilemma by integrating a mixed-models approach using both qualitatively based process information and quantitatively based outcome measures that can encourage program sustainability (Westley, Zimmerman, & Patton, 2006).

Concepts in Complexity Theory

Viewed as the third wave of systems thinking (Williams & Imam, 2006), *complexity* has antecedents in both general systems theory and cybernetics. The first wave – general systems theory - includes the refinement of a developmental ecosystems approach (Bronfenbrenner, 1994). Ecosystems theory builds upon social work's person-in-environment theoretical approach in that people have reciprocal interdependencies with other individuals and their environment (Germain & Gitterman, 1980). Ecosystems use a developmental approach relying on the importance of interactions with micro-systems or settings in which the person lives (Bronfenbrenner, 1994), while stressing the importance of interpersonal learning environments (Germain, 1978). The second wave – cybernetics – uses feedback in order to inform key stakeholders. These lead to the third wave, complexity. Although social work as a discipline was an early adopter of general systems theory, and has applied cybernetics in the maintenance and improvement of social service organizations, it has been late to adopting complexity. This leads to a discussion of how complexity, and its related components are beneficial to social work educators and researchers.

Sensitivity to Initial Conditions of the Agents. This first component parallels well with social work's client-, group-, or grassroots organizational-levels. Complexity modeling begins with the agent, in social work this initial unit of analysis likely remains at the client or family level. A key aspect is determining how these agents function, form relationships with similar agents, make decisions and eventually self-organize. While impacts may come from supervisory influences and higher-ranking positions, within complexity it is at this client level that agents organize.

Attraction. This component attempts to identify what draws clients/agents initially and what maintains their involvement. Variables, or attractors, identify what draws clients or agents together. Adaptation or self-organization aspects include the agents deciding to continue participation, and the formulation of interconnected natural and mutual supports amongst themselves in order to acquire quality of life improvements and career options. For example, when identifying what single factor explained clients continuing their involvement in a faith-based substance abuse treatment program, Wolf-Branigin and Duke (2007) identified involvement in spiritual activities as the key element to remaining active and completing a program. The organization provides a location or identity where agents interact and share information. When applied to social work phenomena, possible examples of organizations include self-help groups, behavioral or physical health providers, educational settings, and services to children and families. The organization refers to the setting or system under which all of these activities occur, in this example the employment readiness program.

Heterogeneity. This component of complexity refers to the array of options within the agent's ecosystem from which the individual agents choose. Environments in which the agents have limited choices, reduces the utility of a complexity approach. Complexity further advances the concepts of ecosystems by having as the researcher's goal: understanding the exigencies that account for more than simple cause and effect explanations to behavior (Bolland & Atherton, 1999). Complexity concerns itself with viewing the complete set of variables affecting client behaviors (Agar, 1999; Halmi, 2003). The heterogeneous organizing component becomes the different program options from which the adolescents and their families choose. This may include these agents' desire to remain active in an employment readiness program, deciding to seek service elsewhere, or deciding not to continue with any service.

Adaptation/Self-organizing. This component refers to an organization's ability to respond to the emerging preferences chosen by agents within the organizations (Strunk, Friedlmayer & Brousek, 2003). For example, needs assessment using spatial (location) data within a complexity approach have included the planning and observation of emergent behavior related to persons with developmental disabilities, physical disabilities, and housing patterns for persons with lowto moderate incomes (Wolf-Branigin, LeRoy & Miller 2001). Advances in computing power and ease of use with software packages encourage new methods of simulating social work phenomena. Occurrences of clusters, also known as hotspots, can further represent self-organization as it relates to both temporal and spatial autocorrelation and variability by exploring both positive and negative organizational feedback mechanisms.

Dynamic Use of Feedback. Most commonly associated with the second wave of systems thought, this vital component determines how systems inform themselves in order to improve decision-making. Positive feedback involves an organization's ability to use information outside of its system, and increases until reaching its useful limits. Negative feedback, most commonly represented as an organization's monitoring or quality assurance process, keeps the organization in equilibrium. To understand the application of this component to complexity theory, envision the push-pull forces that organizations encounter as clients internalize the impacts of the interventions provided, and how program planners use negative and positive feedback in their decisions for future programming. Quality improvement and outcome monitoring methods, vital to improving the efficacy and efficiency of social services, create feedback for both clients and the organization. Feedback includes the agents (clients) sharing information, identifying additional resources and encouraging the other adolescents to remain active and participate in program activities.

*C*omplex systems display dynamic tendencies. These dynamic tendencies include the continually changing environment in which the agents function. Limitations occur when observing dynamic organizational behaviors. While exploratory approaches support social work's person-in-environment paradigm (Padgett, 2004), social work researchers and evaluators need to view the dynamic and continually evolving needs from the client's perspective, or from complexity's agent-based perspective (Buell & Cassidy,(2001). If something is complex, it is relatively unstructured and dynamic (Casti & DePauli, 2000). Examples of dynamic tendencies include the adolescents with disabilities acquiring transitioning skills from childhood to adulthood, persons who abuse substances reconnecting with family members, or immigrant populations acculturating as they strive toward becoming citizens of their communities.

Emergent behavior/Non-linearity. Non-linear dynamics, a key aspect of complexity theory, involves understanding the underlying order of phenomena appearing to lack any pattern or trend. In social service applications, non-linearity includes the chaotic, dynamic and iterative process of clients and their eventual choices (Waldrop, 1993). On a larger organizational scale, this may include the maintenance of an organization or system improvement given the vast diversity of consumers, their demographic and functional characteristics, and services provided (Rhee, 2000). Whether applied on the client or organizational level, non-linearity involves pattern recognition of an emergent behavior.

Statistical Applications for Social Work Research Education

Social work researchers use increasingly advanced statistical techniques; however, these methods often lack the sensitivity to identify emergent self-organizing behaviors. This remains especially true in determining needs of at-risk populations. Broader impacts from the proposed activities must expand on current human service research approaches that focus solely on experimental and quasi-experimental methods. As social work researchers and educators apply complex systems approaches, rigorous methods provide new insights into human service phenomenon.

Methods need to reflect that data analysis within complexity assumes an exploratory or pattern-recognition approach rather than a traditional hypothesis testing or confirmatory approach. Complexity shifts social workers research questions from ones of comparing groups or seeking linear relationships vis-à-vis ANOVA and regression models respectively, to ones that look at trends (e.g., seasonal variation), spatial relationships (clustering on occurrences) and nested phenomena (HLM). Rather than seeking linear relationships or significant group differences, complexity applies statistical methods of predicting group membership (e.g., discriminate functions), identifying underlying structure (e.g., exploratory factor analysis), or discerning a time course of events (Tabachnick & Fidell, 2001). This framework provides for the development of spatial methods to predict and quantify social work phenomena within often apparently chaotic environments. Figure 1 summarizes these statistical approaches as related to the components and are discussed in detail below. Exhibit 1 applies several of these concepts to a social service organization providing support services to persons with intellectual and developmental disabilities.

Measuring sensitivity to initial conditions. Multiple software options are available. In addition to using MS Excel or SPSS for basic descriptive and inferential statistics, appropriate and rigorous analysis benefit from additional software packages for assessing autocorrelation and emergent behavior. On a qualitative level, the importance of images includes developing concept maps, eco-maps or other displays that assist in visualization. *Microsoft Visio* software provides a simple drag and drop approach for creating graphical and visual representations.

Attraction. In addition to descriptive and inferential statistics, data analysis in an emergence framework may focus on either simple autocorrelation or spatial autocorrelation. Autocorrelation determines how surrounding observations affect the unit under study, while spatial autocorrelation more specifically applies two- or three-dimensional space within a spatial econometric approach. The choice of a spatial econometric approach occurred because of technique's expansion of temporal autocorrelation methods. In this agent-based approach, location information at each time interval is plotted into a two dimensional space for conducting the autocorrelation analysis (Anselin, Florax & Rey, 2004).

Heterogeneity. Bayesian decision trees provide one means to identifying and assigning the probabilities of differing paths that agents choose. Three concepts are useful to understanding Bayesian methods: 1) prior probability refers to the assumption that the model is true prior to data collection, 2) posterior probability refers to the probability that a model is correct after data collection, and 3) the likelihood describes the conditional probability of the data assuming the model that had been developed (Lee, 2004). Compared to classical inferential statistical methods, Bayesian probabilistic inference enables decision-making based on information by evaluating the probable success of a model (or set of models) given the available observed data and to develop conclusions using known sample data. For example, individuals seeking substance abuse treatment with multiple issues will follow differing treatment pathways based on issues such as a co-occurring mental illness, involvement in legal systems or family dysfunction being present.

Dynamic Use of Feedback. Two statistical methods appear useful, survival analysis and network analysis. Survival analysis provides a useful technique for identifying why some agents self-organize and others do not. Network analysis, also known as social network analysis, seeks to identify the relationships between agents (Wasserman & Faust, 1994). This approach provides a useful method in understanding the flows of information, in this instance the feedback in maintaining a system, between interconnected agents.

Adapting/Self-organizing. Two advanced statistical methods, k-means cluster analysis and structural equation modeling, apply. First, k-means cluster analysis, explores whether natural groupings or clusters appear. It uses a log-likelihood distance measure in order to create probability distributions of the variables. The clustering criterion assesses whether the agents are spatially dependent on others within each location (Bailey & Gatrell, 1995). The second approach for measuring adaptation/self-organization, structural equation modeling (SEM), produces latent variables based on several observable variables in order to represent an abstract concept. While SEM typically serves a confirmatory approach to modeling, it can also be exploratory (Bollen, 1989). The approach's strength lies analyzing the covariances of multiple variables, rather than individual observations.

Emergent Behavior/Non-linearity. Emergence represents the self-organizing behavior of human service consumers. Measuring emergence, as represented by various temporal and spatial autocorrelation indices plays a vital role (Morowitz, 2002). Within complexity, spatial data serve as an extension of time series data in order to identify emergence. Applying the emergence concept provides an approach for organizational level inquiry because of the physical attributes and patterns resulting from human service interventions (Hudson, 2000).

The first approach, spatial analysis includes several methods and related software packages. Within spatial analysis, we typically seek pattern recognition or identify clustering by using spatial autocorrelation. Spatial autocorrelation - similar to linear correlation, but interested in identifying clusters of observations rather than a line – quantifies the influence of surrounding observations on our unit of analysis, the agent or client. One in particular software package, *TerraSeer*, visualizes patterns and quantifies significant clustering in data. The *SpaceStat* features within the *TerraSeer* package allows for the creation of spatial econometric modeling and the creation of local patterns of spatial association and create simulations. These packages allow for geographic information systems (GIS) to be included.

Latent growth modeling (Meredith & Tisak, 1990), another form of SEM, estimates individual/agent-based longitudinal growth trajectories. This modeling method uses repeated measures of the dependent variable as a function of a causal and complex process. Latent growth modeling has applications when investigating both system growth and change.

More advanced researchers wanting to create agent-based models and simulate interactions given the existing longitudinal data sets, should consider using *NetLogo* (2007), *SWARM* (2007) *or Multi-Agent Simulator of Neighborhoods* (MASON, 2007) software. These freely distributed software programs simulate multi-agent complex systems. Some advanced computational and programming skills will be useful because these programs require a basic knowledge of computer modeling. Technical support and tutorials are available from their websites.

Conclusions

Complexity models are highly dependent on using temporal and spatial data. So, is the application of complexity only using qualitative methods to create a hypothesis to be tested later via quantitative methods? Social work managers and planners typically live in a quantitative world, whereas practitioners are in a qualitative world. Studying human environment interactions frequently do not consider individual-level or cross-discipline data, often resulting in weak explanatory and predictive power (An, Linderman, Qi, Shortridge, & Liu, 2005).

Given social works' person-in-environment foundation, the potential use of agent-based modeling respects the viewpoints and decisions made at the client level, while simultaneously understanding that these activities occur within an organizational body. Potential applications within the social services cover a broad range. These applications may include developing historical analyses, understanding emerging social phenomena, understanding indigenous populations, to applying trajectory growth curves in clinical trials.

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Figure 1

Statistical Methods Components and their Application

Complexity Component	**Relevance**	**Suggested Statistical Method**
Sensitivity to initial conditions	Discerning background of the agents/clients	Simple descriptive statistics (e.g., Excel, SPSS)
Attraction	Identifying the factors that attract and maintain client involvement	Autocorrelation
Heterogeneity	Identifying choices available and made	Bayesian decision trees
Dynamic Use of Feedback	Delineating how information flows and decisions made	Network analysis Survival analysis
Adapting/Self-organizing	Identifying patterns of agents	Cluster analysis Structural Equation modeling
Emergent Behavior/Non-linearity	Identifying outcomes of social work phenomena	Spatial analysis Latent growth modeling Agent-based modeling

Exhibit 1

Case Example of an Organization Providing Support Services to Persons with Disabilities

In this brief example, a support services organization providing health, education and housing services to adults and adolescents with intellectual and developmental disabilities wanted to know whether their efforts to have persons physically integrated into their county were successful. First, they needed to know the organization's current functioning level. Administrators compiled descriptive statistics from their management information system. These client characteristics included the geographic location of their home, type of living arrangement (e.g., group home, independent living, and semi-independent living), level of family support, and employment/education status.

Identifying what attracted these individuals included the locations of the person's home - in relation to public transportation lines, near others/family members - involved spatial autocorrelation. Specifically, the *Moran's I* statistic (Wolf-Branigin, LeRoy & Miller (2001), measured the influences of others with disabilities living nearby. Understanding how clients self-organized included several characteristics identified from the descriptive statistics in a cluster analysis. Finally, agent-based modeling will aid in understanding how this leads to a collective emergent behavior. By using a simulation software program (e.g., NetLogo) allows us to include the current locations where persons with Because the county does not allow another group home within 500 feet of another, this places a rule or constraint on the model.