Closing the Micro-Macro Divide in Modeling Technology Adoption

Erica Briscoe[1], Ethan Trewhitt[1], C.J. Hutto[1]

[1] Georgia Tech Research Institute Atlanta, GA
{Erica.Briscoe, Ethan.Trewhitt, Clayton.Hutto}@gtri.gatech.edu

Abstract. The adoption of new technology depends on many factors, such as the type of technology, the context or culture in which the technology is introduced, and the individual decisions by people within that culture. This work presents the advantages provided by using a multi-scale modeling approach to represent human adoption behavior of e-commerce. This approach uses an agent-based model to encompass the detailed behavior of individuals and their immediate network of relationships, as well as an influence-based system dynamics model to show how society-level influences function interactively and with respect to individual agents. The exploration of technology adoption grounds the model in a realistic environment and allows the incorporation of theoretical models from multiple relevant domains. The integrated model demonstrates how representing behavior at multiple levels of abstraction is a natural approach that allows for a greater understanding of the relationship of influences across sociological scales.

Keywords: multi-scale modeling, agent-based modeling, system dynamics, technology adoption

1 Introduction

Evident throughout the social sciences [1] and often referred to as the "micro-to-macro problem" [2][3], the micro-macro divide concerns the capacity for theory to explain the relationship between the constitutive elements of social systems (individual, micro-level cognitive agents) and the emergent phenomena that result from their interaction on larger scales, such as organizations (at the meso level), and whole societies (at the macro level). This divide has led to approaches that concentrate, and thus may restrict, scientific study by scoping investigations to emphasize cognitive, social, or sociological perspectives. Attempts to scale micro-level models to the society level are troublesome because small variations at the micro scale become inappropriately magnified at the macro-scale. On the other hand, macro-level models often use aggregate data that "hides" potentially insightful activity that would typically be observed at the micro-scale. To overcome these limitations, theoretically grounded models of human cognition should be paired with those that account for the influence of interpersonal interactions, as well as representations of how these individual and group interactions emerge to form phenomena reflected at the society level.

An excellent example of multiple-scale behavior is the spread and adoption of new technology. New technologies are traditionally 'diffused' among members of a social system through communication mediums over time. Diffusion, in this sense, is a special type of communication concerned with the spread of messages that are perceived as new ideas. Diffusion of Innovations theory [4], in which an innovation is an idea or technology perceived as new by the individual, proposes that this spread creates a distinct pattern of innovation adoption (see Fig. 1). This pattern has led to the identification of five adopter categories for members of a social system: innovators, early adopters, early majority, late majority, and laggards.

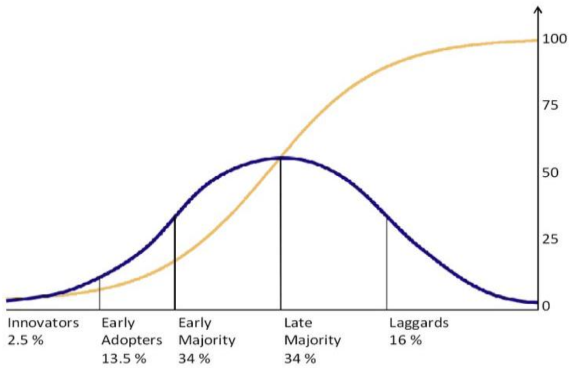


Fig. 1. The 'S' shaped curve represents the cumulative rate of adoption (or diffusion curve). The bell curve depicts the number of new adopters along the same timeline.

Though various theories exist to explain the spread of technological innovations (e.g., the technology adoption lifecycle [5][6] and the Technology Acceptance Model [7]), it has been noted that many theories lack an adequate account of the various types of influence [8], such as cultural influence (e.g. [9]). Newer, composite theories may prove to be more predictive. The Unified Theory of Acceptance and Use of Technology (UTAUT) combines eight of the most prominent technology acceptance models [10]. Most relevant work, however, fails to incorporate a perspective that captures the combination of individual and group (micro- and macro-) interactions that provide significant influence on human behavior (see [11] for a similar multi-scale argument).

With the UTAUT as the theoretical basis for integration, this work presents a multi-scale model to represent the effect of influence on the adoption of electronic commerce (e-commerce) at interrelated levels of human socio-cognitive and cultural behavior. At the intra-individual level, a belief-based model is used to represent cognitive behavior. Using elements of network theory [12], social relationships are captured at an interpersonal level and likewise represented in the agent-based model (see [13] for a description of agent models). At the societal level, a system dynamics model is used to represent macro-level influences of technology acceptance. These models are linked so as to exchange information by having macro-level influences feed into the micro-scale agent-based models, while the aggregation of individual behaviors supply input to the macro-scale system dynamics model. This interaction allows for a natural and comprehensive representation of the various factors that influence technology adoption.

2 Intra-individual Representation

Because the domain of technology adoption, especially as it relates to social influence, largely involves the existence and communication of personal attitudes and beliefs (e.g., attitudes regarding expectations of performance of the technology or the effort needed to use the technology), the model used to represent cognitive decision-making does so in terms of the interactions of a set of parameters associated with beliefs. These beliefs are represented as nodes within a network where vertices (nodes) represent individual belief propositions held by an agent, and edges (links/lines/arcs/connections) represent relationships between beliefs; they are usually weighted and may be directed (see [14] for an introduction to graph theory and its relationship to social networks). As with other network-oriented perspectives of cognition (e.g. [15]), beliefs are represented as a pairing of cognitive concepts. The resulting *belief network* creates a framework for studying the social transmission and subsequent use of knowledge resulting from agents' processing of information.

The set of interrelated beliefs used in the presented model should be familiar to researchers in the area of technology acceptance. The specific beliefs are based on the work by Venkatesh et. al. [10]. Their UTAUT model combines eight of the most prominent technology-acceptance models observed in the literature and provides a definitive list of variables that are critically relevant to an individual's Behavioral Intention (BI) and Use Behavior (UB) for adopting a new technology, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC) and Voluntariness of Use (VoU). Fig. 2 depicts the notional belief network used for this cognitive network model, as well as the derived edge weights (derived from [10]) used in the relevant governing functions for belief dependencies.

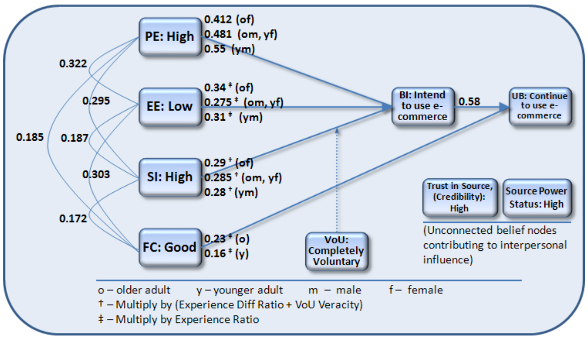


Fig. 2. Conceptual rendering of the agent belief network for adoption of e-commerce (based on [10]).

3 Inter-individual Representation

To depict the interpersonal level of the multi-scale modeling spectrum described in this work, a similar network-based approached is used. Here, network vertices are individual human agents, and network edges are the cognitive ties (commonly shared beliefs), communication links, and social relationships between them. Interpersonal tie strength [16] forms the basis for the degree of influence one individual has over another. In the current model, tie strength is taken to be an index for interpersonal influence, and is quantified according to equation 1:

$$TS_{ij} = (1 - \alpha_{ij}) \qquad (1)$$

Where TS_{ij} is the directed tie strength index representing the degree of influence that person i has over person j (which determines the degree to which j adopts i's views about each of the propositions in the belief network). The term α_{ij} is a score between 0 and 1 that represents the normalized cognitive distance between person i and person j, as measured by the difference with which individuals i and j accept the propositions within the belief network (the cognitive distance of the pair is normalized relative to their individual differences compared to every other person within their own social networks). Thus, the more similar individual i is to j in terms of their attitudes across all the propositions in the belief network, the more influential j will be on swaying i's position with respect to any particular proposition node.

4 The Societal Model

To represent high-level societal factors that contribute to the adoption of technology (specifically, e-commerce) a system dynamics approach is used. A system dynamics model is a type of executable model used to represent and understand the dynamic behavior of a complex system over time [17]. Complex systems often exhibit highly non-linear behavior where the relationship between cause and effect is not intuitively evident. System dynamics models use stocks and flows to represent system elements and their relative influences upon each other. Stocks represent an inventory of accumulated entities (e.g., money) and are indicated in the e-commerce adoption model using rectangular boxes (see Fig. 3). Flows are indicated by double-lined arrows, and show how entities move between stocks or between a stock and a cloud.

Fig. 3 depicts a system dynamics model that captures the critical variables involved with the adoption of e-commerce. This particular model concentrates on three areas: economic variables related to selling a product on the internet, domain-specific variables to e-commerce (e.g. marketing), and cultural variables of the society in which the technology is introduced. While not an exhaustive list, these variables were selected as most significantly influential on system-level and micro-level behavior. As seen in Fig. 3, these three areas are somewhat isolated from other system variables. This isolation is indicative of another benefit to this type of multi-scaled modeling, where independent models may be 'swapped' as needed or as a means of evaluating different theories.

This society-wide model is also valuable in that it allows for the exploration of feedback relationships within the system. For example, in this model, the number of e-customers affects the demand schedule - the amount of some good that buyers are willing and able to purchase at various prices. The demand schedule, then, determines prices which customers use to compare to the price of goods which could be purchased from traditional (non-electronic commerce) retailers. This comparison influences the individuals' choice to adopt e-commerce, which leads to a change in the number of e-commerce customers, completing the loop.

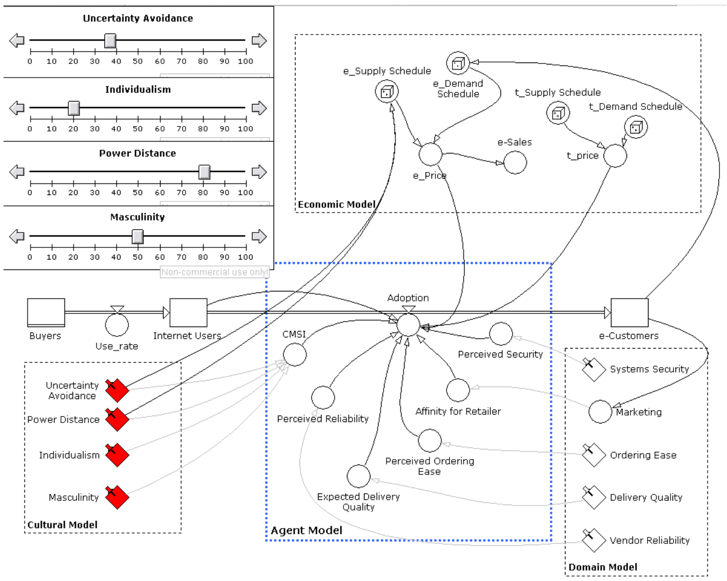


Fig. 3. System dynamics model of macro-level variables in technology adoption

The cultural portion of the macro model is integral to fully capture the significant influence of cultural context on technological decisions. Hofstede's [18] dimensions of national culture are widely used by cross-cultural research and specifically for technology adoption (e.g. [19]). For example, cultures high in uncertainty avoidance, power distance and masculinity and low in individualism are expected to be less accepting of computer-based media. To capture this influence, the Computer-based Media Support Index (CMSI) was developed to express the comprehensive influence of all four dimensions on technology acceptance ([19] and is thus included in the model as a mediating variable according to its specific influence on adoption in conjunction with variables included in UTAUT (see [20] for supporting studies). Additionally, culture has economic-related effects, for example, inventory levels are influence by power distance and uncertainty avoidance [21].

The e-commerce domain-specific variables are captured based on the features found most important to those evaluating their use of e-commerce [22]. As seen in Fig. 3, these variables feed directly into individuals' perceptions (in the agent model) of critical aspects related to their beliefs about e-commerce.

5 Model Integration and Execution

Fig. 4 shows the composition of the two models as they execute three levels of simulation. Both the agent-based model (ABM) and system dynamics (SD) model operate on a common timeline, in which a single timestep in either model represents the passage of an equal quantity of time. The two models periodically share relevant variable values and retrieve the necessary dependencies using a shared memory space. In this implementation, a standard relational database is used as a structured log upon which each model writes its useful output values and reads as input the values written by the other model. A distinct table stores the variable log of each model; each record contains a timestamp, variable name, and variable value. Each model chooses how often to write to the log and how often to read from it; typically a log value is written or read every 1-10 timesteps. Synchronization frequency depends upon the desired balance between the system's performance needs and each model's sensitivity to frequent changes to inputs and outputs, as well as the real-world duration represented by a timestep.

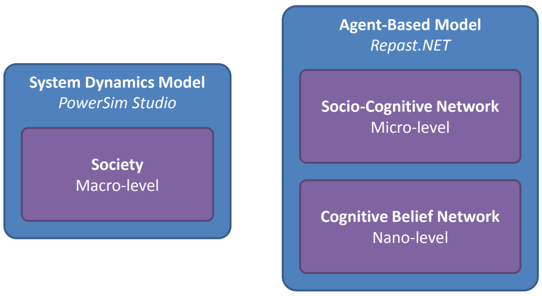


Fig. 4. Models and their associated levels of representation

Fig. 5 shows the basic interaction between the models. The models execute simultaneously, periodically exchanging information with the database. If one model stalls, the other will eventually stall as well in order to preserve causality. Each model includes a t_{max} parameter that specifies the maximum number of timesteps that the model will execute without an update from the other model. If one model is sensitive to subtle changes in the output of the other model, $t_{max} = 1$ ensures the greatest accuracy at the cost of performance. If models are less sensitive, greater values of t_{max} will reduce synchronization overhead and improve performance.

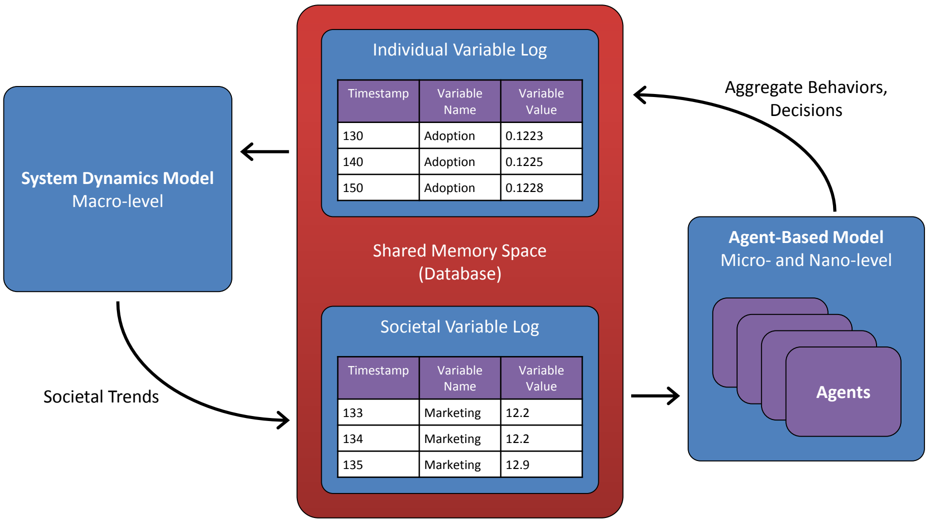


Fig. 5. Interaction between models using a shared memory space

6 Model Demonstration and Results

The most obvious benefit to developing and executing an integrated model is that it provides the potential to represent the interaction between multiple levels of influence. For example, an investigation may involve how an advertising campaign targeting a particular demographic will influence the e-commerce retail sales of a given product. The effect of a marketing campaign (psychological persuasion) could be evaluated at both the individual level (e.g., how the campaign altered the individuals' beliefs), at the inter-personal level (e.g., how the influence of the campaign translated into influence between individuals), and at the societal level (e.g., did the demand for the product cause an increase in the number of retailers competing for e-commerce customers).

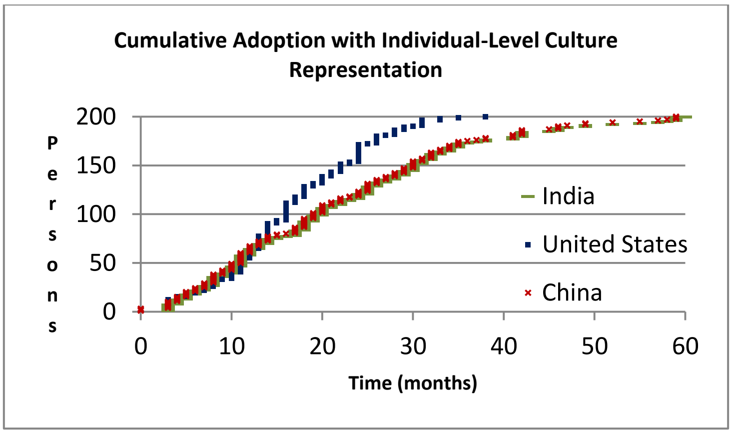
To demonstrate the usefulness of the integrated, multi-scaled approach, we depict how the influence of macro-level variables (e.g. culture) manifest at multiple levels of representation, which effectively (and simultaneously) encourage, reinforce or suppress decision-making behavior at the level of the individual agent. To that end, we ran the model under three conditions and across three different cultures, the United States, China, and India, with the models 'sharing' information as indicated by the arrows that cross the 'Agent Model' boundary in Fig. 3 every 10 time-steps.

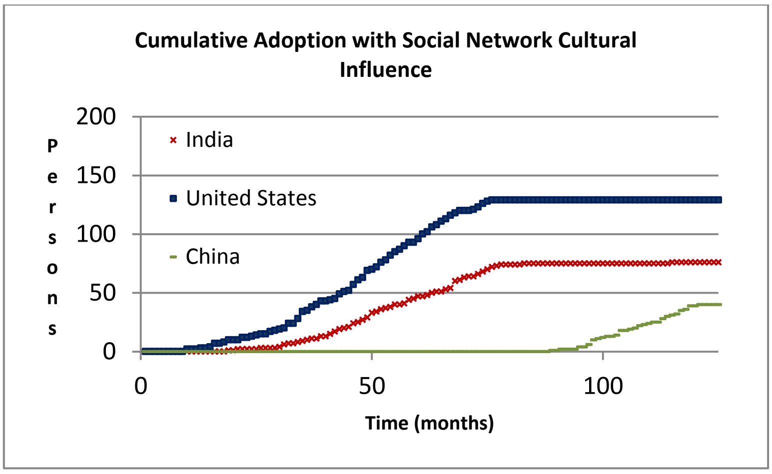
The top graph in Fig. 6 depicts the graphed cumulative adoption for the three countries where culture is used *only* as an input in the decision-making process of the agents (a randomly selected group of 10 at every time step) through the CMSI variable previously described [19][20]. In this simulation, each agent in a 200 agent population communicates with 10 randomly determined agents at every time step.

The adoption curves are strikingly similar across cultures, where, here, adoption behavior is simulated using only a 'nano'-level theory.

The middle graph in Fig. 6, depicts the adoption results when the model is run with the incorporation of culture to create a more realistic social network for each agent. Here, the connections (by which beliefs are shared) between individuals are instantiated using a method similar to the Watts and Strogatz [23] small-world network model. Each agent (of the 200) is connected to its 10 nearest neighbors by edges, where proximity is determined by both cognitive and social similarity (randomly set at agent instantiation). We use a similarity measure to create the network so as to generate homophily, the tendency of individuals to associate disproportionately with others who are similar to themselves [24]. Then, each edge is randomly rewired with probability p by disconnecting one of its vertices and connecting it to a randomly chosen vertex. P, in this sense, indicates the randomness of the network and is determined by the *Individualism* dimension, devised to indicate the cohesion of 'in-groups' within a society [18], provided by the societal model. It is of no surprise that this model produces much more adoption differentiation between cultures, where the United States has the highest level of Individualism, followed by India, then China (91, 48, and 20, respectively). It also demonstrates the propensity for certain agents to never reach a state of adoption, either through the isolation afforded by their social networks *or* as resulting from the total number of e-commerce users (in the societal model) never reaching a large enough number to push down prices in the economic model.

The bottom graph in Fig. 5 includes the influence of culture in a fully multi-scaled approach. Here, culture affects inventory and pricing models [21] (macro-level), the cohesion of groups in the social networks [18] (micro-level), and individuals' intentions (nano-level), thereby combining related adoption theories across multiple scales. This type of representation creates a model of adoption behavior with the ability to capture interaction effects across scales that would likely be missed using a single-scaled model.





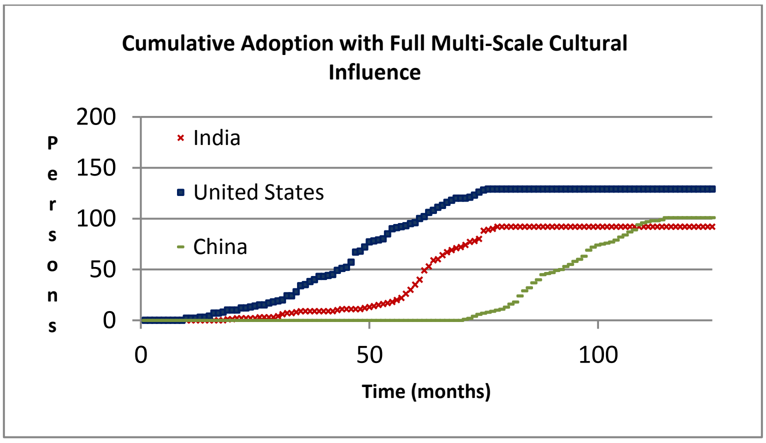


Fig. 6. Output from a model of e-commerce adoption across three cultures run under three conditions. The top graph represents cultural influence as an input to only the agent's intention model. The middle graph represents the influence of culture in the formation of social networks-which influences information dissemination. The bottom graph represents the output from the inclusion of culture at multiple scales in the model, which provides both the expected s-curves typical of adoption and cross-cultural variability.

7 Future Work and Conclusion

This paper has presented an investigation into the development of an integrated, multi-scale modeling approach that captures human cognitive, social, and cultural components of human behavior using the adoption of e-commerce as a domain of demonstration. The breadth of this work creates many avenues for further research.

Currently, we are designing experimental research to further develop the micro-level cognitive models. This work will investigate how social relationships affect the spread of ideas (represented as beliefs) according to network models described above. As previously noted, this approach is adaptable by "swapping" theoretical constructs, and to that end, we plan to incorporate a variety of economic models to evaluate their effect on adoption rates. While e-commerce is our current domain of demonstration, we anticipate additional evaluations for technologies that have not met with widespread success, as these cases may be less reliant on communication patterns and more related to other variables, such as culture. Additionally, we anticipate the need for analysis that uses open-source data (e.g. social media) to determine network structure across various cultures and mediums and that may provide additional insight into how beliefs and influence are transmitted.

This work has presented an approach that uses a multi-scaled model that exchanges relevant information across representational scales in order to demonstrate the pairing of theoretically grounded models of human cognition with those that account for the influence of interpersonal interactions and with representations of emergent individual and group phenomena at the societal level. The proposed system combines these two model types using specific interaction points to create a single integrated behavioral model. This approach is intended to overcome some of the limitations that are imposed by utilizing a single-scaled model. For example, the overloading of single-scaled models with large numbers of independent variables, a criticism of current technology adoption models [26]. Finally, this federated approach provides a means of examining various theoretical approaches and is extensible to modeling human behavior related to other activities beyond technology adoption.

References

1. Goldspink, C., Kay, R.: Bridging the Micro–Macro Divide: A New Basis for Social Science. Human Relations 57, 597--618 (2004)
2. Coleman, J. S.: Foundations of social theory. Belknap Press of Harvard University Press, Cambridge, MA (1994)
3. Smith, T. S.: Non-linear dynamics and the micro–macro bridge. In: Eve, R. Horsfall, S., Lee, M. (eds.) Chaos, complexity and sociology. Sage, Thousand Oaks (1997)
4. Rogers, E. M.: Diffusion of innovations. Free Press, New York (1995)
5. Beal, G., Rogers, E., Bohlen, J.: Validity of the concept of stages in the adoption process. Rural Sociology 22, 166--168 (1957)
6. Rogers, E.: Diffusion of Innovations. Free Press, New York (1962)
7. Davis, F.D.: A technology acceptance model for empirically testing new end-user information systems: theory and results. Doctoral dissertation. Sloan School of Management, MIT, Cambridge (1986)
8. Davis, F., Bagozzi, R., Warshaw, P.: User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. Management Science 35, 982--1003 (1989)
9. Zakour, B.A.: Cultural difference and information technology acceptance. Proc. of the 7th Annual Conference of the Southern Association for Info. Sys., 156--161 (2004)
10. Venkatesh, V., Morris, M. G., Davis, G.B, Davis, F.D.: User acceptance of information technology: Toward a unified view. MIS Quarterly 27, 425--478 (2003)
11. Goldstone, R.L., Janssen, M.A.: Computational models of collective behavior. Trends in Cognitive Science 9, 424--430 (2005)

12. Wasserman, S., Faust, K.: Social Network Analysis: Methods and Applications (Structural Analysis in the Social Sciences). Cambridge University Press, Cambridge (1994)
13. Bonabeau, E.: Agent-based modeling: methods and techniques for simulating human systems. PNAS 99, 7280--7287 (2002)
14. Easley, D., Kleinberg, J.: Networks, Crowds, and Markets: Reasoning About a Highly Connected World. Cambridge University Press, Cambridge (2010)
15. Carley, K.: The Value of Cognitive foundations for Dynamic Social Theory. J. of Mathematical Sociology 14, 171--208 (1989)
16. Granovetter, M. S.: The Strength of Weak Ties. The American Journal of Sociology 78, 1360--1380 (1973)
17. Sterman, J.: Business Dynamics: Systems Thinking and Modeling for a Complex World. McGraw-Hill/Irwin, Boston (2002)
18. Hofstede, G.: Culture's Consequences: comparing values, behaviors, institutions, and organizations across nations (2nd ed). SAGE Publications, Thousand Oaks (2001)
19. Straub, D., Keil, D., Brenner, W.: Testing the Technology Acceptance Model across Cultures: A Three Country Study. Information & Management 31, 1--11 (1997)
20. Slyke, C. V., Lou, H., Belanger, F., Sridhar, V.: The Influence of Culture on Consumer-Oriented Electronic Commerce Adoption. Proc. of the 7th Annual Conf. of the Southern Association for Information Systems, 310--315 (2004)
21. Oral, E., Mistikoglu, G., Erdis, E.: JIT in developing countries-a case study of the Turkish prefabrication sector. Building and Environment 38, 853--860 (2003)
22. GVUs 8th WWW user survey, http://www.cc.gatech.edu/gvu/user_surveys(1997)
23. Watts, D., Strogatz, S.: Collective Dynamics of `Small-World' Networks. Nature 393, 440--442 (1998)
24. Lazarsfeld, P., Merton, R.: Friendship as social process: A substantive and methodological analysis. In: Berger, M., Abel, T., Page, C. (eds.) Freedom and control in modern society pp. 18--66. Nostrand, New York (1954)
25. Hermeking, M.: Culture and Internet consumption: Contributions from cross-cultural marketing and advertising research. J. of Computer-Mediated Communication 11, article 10 (2005)
26. Bagozzi, R.P.: The Legacy of the Technology Acceptance Model and a Proposal for a Paradigm Shift. J. of the Association for Info. Systems 8, 244--254 (2007)