Volume 2, Issue 4, April 2015, PP 199-210
ISSN 2349-0373 (Print) & ISSN 2349-0381 (Online)
www.arcjournals.org

International Journal of Humanities Social Sciences and Education (IJHSSE)

The Application Trends of the Agent-Based Modeling Literature

Chen-Wo Kuo
Dept. of Exhibition and Information Service, National Palace Museum, Taipei, Taiwan (R.O.C), paulkuo@npm.gov.tw

Yu-Hsiang Yang
Dept. of Exhibition and Information Service, National Palace Museum, Taipei, Taiwan (R.O.C), syang101@npm.gov.tw

Abstract
Agent-based modeling (ABM) refers to the computer simulation of agents (representing individual roles) in a dynamic social system. The purpose of this study is to shed light on the application trends of the international literature related to ABM on the SSCI database between 1995 and 2014 using a bibliometric technique and a growing hierarchical self-organizing map (GHSOM). The results of this study reveal that interest in the international literature related to ABM continues to expand. The results of the GHSOM identify that the main topics of the literature related to ABM include complexity theory, prisoner's dilemma, altruism, cooperation, land-use change, cellular-automata, stock market, innovation diffusion, and cooperation.

Keywords: Agent-Based Modeling, ABM, Bibliometrics, GHSOM, Growing Hierarchical Self-Organizing Map.

1. INTRODUCTION

Agent-based modeling (ABM), or the multi-agent system, refers to the computer simulation of agents (representing individual roles) in a dynamic social system. Here, agents refer to different "representatives" who interact with each other or with the environment on the basis of pre-established rules. The "agent" is able to produce a series of environmental awareness practices (percept sequence) and actions. Rational agents can be expected to achieve optimal performance that is the result of a series of perceptions in addition to their internal knowledge.

Beginning in the 1940s, John von Neumann, the founder of computer architecture, struggled with a kinematic model of automata afloat in a sea of raw material; however, he failed to capture the essential logic of self-reproduction with this model. After adopting a suggestion from his colleague, Stanislaw Ulam, he proved that the collective dynamics resulting from such simple rules may bear a formal resemblance to the biological process of self-reproduction and evolution [1, 2]. Spatial agent-based models were originally implemented in the form of cellular automata such as Conway's Game of Life [3]. Cellular automata represent agent interaction patterns and available local information by using a grid or lattice environment [4].

On the other hand, derived from the Schelling Segregation Model [5], ABM focuses on the value of beginning with rules of behavior for individuals and using simulation to discover the implications of these rules for large-scale outcomes. Thomas Schelling, the winner of the 2005 Nobel Memorial Prize in Economic Sciences (shared with Robert Aumann), called this "micromotives and macrobehavior" [6]. ABM has been applied in multiple disciplines, such as economics, physics, biology, and ecology, to explore the phenomenon of complex adaptive systems (CAS), and it has gradually been more widely used in almost every field of study for a deeper understanding of its particular phenomena. For instance, an economic system in agent-based economics can be composed of heterogeneous agents, and those summation variables are the results of interactions between these heterogeneous agents. Unlike the "top-down" mode of thinking in traditional macroeconomics, ABM has introduced a "bottom-up" style of thinking to macroeconomics under a new paradigm, one which presents a challenge to most economists

[7, 8]. Thus, ABM serves as an ideal tool for us to advance our thinking from the micro to the macro perspective and to observe the links and relationships between these two levels [9].

The explorations of the ABM literature have seen vigorous development in the last decade owing to the convenience and advancements of ABM tools. Meyer, Lorscheid, and Troitzsch (2009), for example, used a co-citation method to review social simulation [11], while Zenobla, Weber, and Daim (2009) assessed artificial markets using SWOT (Strengths, Weaknesses/Limitations, Opportunities, and Threats) analysis [11]. Until now, no overall analysis of ABM has been conducted despite a plethora of research successfully applying bibliometric analysis to a number of multidisciplinary fields, such as the management of technology [13], new technology creation activity [14], venture capital [15], and university-industry collaboration in Italy [16].

The purpose of this paper is to assess how ABM affects social science as a technological innovation tool. To elucidate the ABM application trends, we explored ABM technological trends and forecasts by means of bibliometric reviews of the literature in the SSCI (Social Science Citation Index) database between 1995 and 2014. Standard bibliometric indicators such as the number of papers, number of authors, productivity by country, institutional collaboration, and most cited articles were analyzed. To reveal the major topics of articles related to ABM, we adopted the growing hierarchical self-organizing map (GHSOM) approach [17, 18] to cluster the conceptual topics into a hierarchical representation of dynamic 2-dimensional interrelated structures within the data. Through the topic analysis of the ABM literature, the study will also indicate the future trend of the ABM application.

2. DATASET AND METHOD

2.1 Data

The dataset used in this study was derived from the SSCI database of the Web of Science, created by the Institute for Scientific Information. The SSCI database comprehensively indexes over 1,950 journals across 50 social science disciplines. It also indexes individually selected, relevant items from over 3,300 of the world's leading scientific and technical journals.

An empirical search command was used by Topic=("agent-based model*") OR Topic=("agent-based system*") OR Topic=("agent-based simulation*") OR Topic=("multi-agent simulation*") OR Topic=("multi-agent system*") refined by Document Type= (ARTICLE OR REVIEW) to retrieve data related to ABM. The documents specifically included articles and reviews in the study. Book reviews, papers of the proceeding, letters, notes, and meeting abstracts were not taken into consideration. A total of 2,547 papers published between 1995 and 2014 were found.

2.2 Method

A co-occurrence analysis of document content is usually performed on substantive keywords appearing in a bibliographic database record field such as the title, descriptors, or abstract. These fields encapsulate the topicality of a document, although keywords from the body of the text could be used as well [19]. The benefits of co-word analysis can be mixed depending on the application, such as clustering major topics of a large collection of documents on the basis of their content and providing a topical landscape of a field. Many studies, such as [20-25], applied informetric maps using co-word analysis to visualize cognitive structures on the basis of scientific topics and the relationships that link them.

Co-word analysis embraces a large number of different methods to determine the clusters of word co-occurrence. For the purposes of the present study, we choose GHSOM, which has been used successfully before in comparable studies, to identify distinctive clusters of papers [26, 27].

The self-organizing maps were designed according to the concept of unsupervised artificial neural networks to process high-dimensional data and provide visual results [24, 28-30]. However, SOM requires a predefined number of nodes (neural processing units), and it implements a static architecture. These nodes result in a representation of hierarchical relationships with limited capability. The GHSOM approach was developed to overcome these limitations, and therefore, it is often applied in the field the information extraction [17, 18, 26, 27, 31]. The GHSOM is based on the characteristic of SOM, but it can automatically grow its own multi-layer hierarchical structure in which each layer encompasses a number of SOMs, as shown in Figure 1.

The process of applying the GHSOM to topic analysis is illustrated in Figure 2. The three phases are the data preprocessing phase, the clustering phase, and the interpreting phase.

Fig 1 Structures of GHSOM [18]

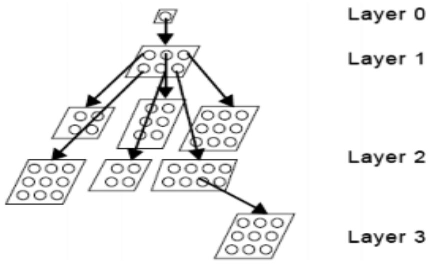
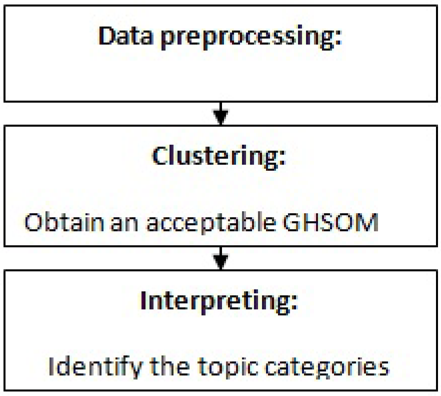


Fig 2. The three phases of the topic analysis process.



In the data preprocessing phase, key terms, such as titles, keywords, and subject categories, are used to represent the content of the documents. Meaningful key terms describing the articles are extracted directly from the documents without any manual intervention. These key terms are weighted according to a *tf* x *idf* state-of-the-art weighting scheme, as in equation (1) [18, 19, 26, 32].

$$\mathbf{w_i(d) = tf_i\,(d) \times log\,(N / df_i)} \quad \mathbf{(1)}$$

In equation (1), $w_i(d)$ represents the weight of the *i*th term in document (d), tf_i (d) represents the number of times that the *i*th term appears in document, (d) N represents the total number of documents, and df_i represents how many documents contain the *i*th term. The weighted value for a term will always be greater than or equal to zero. This weighting scheme assigns high values to terms considered important for describing the content of a document and discriminating between various documents. A high weight is earned by frequent appearances of a term in a given document with infrequent appearances of terms within the entire collection of documents. In this manner, weight assignment tends to filter out common terms. On the basis of the weighting values, we selected the top order distinct key terms for document representation [19, 32]. The resulting key-term vectors were used for the GHSOM training.

In the clustering phase, the GHSOM experiment was conducted through the trial and error method using various values for breadth and depth and different normalizations to gain an acceptable GHSOM model for the analysis. The results of the GHSOM are shown as Figure 2.

In the interpreting phase, for each node of the GHSOM in the first-layer and some nodes of the second-layer, which will be re-grouped into layer 3, we counted the df_i value of each key term in all articles, clustered them into a particular node and assigned a key term with the highest df_i value (or several key terms if their df_i values were very close) as the topic category. The important key terms are then automatically assigned by the GHSOM using the *tf* x *idf* weighting scheme.

3. RESULTS

3.1 Overview of Productivity

A total of 2,547 papers related to ABM were retrieved from the SSCI database. Figure 3 shows the number of published papers on the topic of ABM between 1995 and 2014. According to the numerical data, a large number of research papers published in 2012, 2013, and 2014 have been catalogued in the SSCI database, with distribution rates of 294 (11.54%), 354 (13.9%), and 415 (16.29%) against the total number of papers, respectively. It has also been observed that a trend in the growth of these numbers appears to have begun in 2004. Figure 4 shows the number of citations of published papers related to ABM made each year. The figures suggest that the number of these citations has also been increasing. Clearly, the topic of ABM has received a great deal of attention from researchers.

Fig 3. Number of published papers from 1995 to 2014

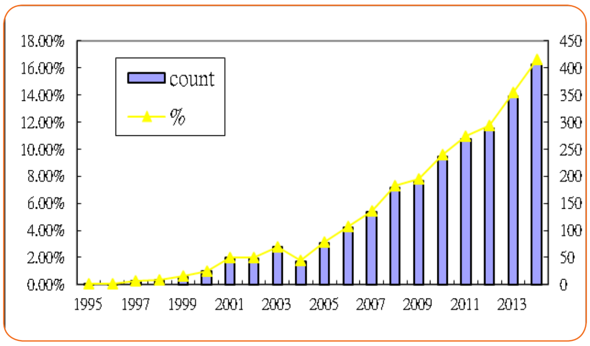


Figure 5 illustrates the ten countries ranked as the top publishers of catalogues in the SSCI database. The figure shows that the USA was the dominant country, followed by England and Germany.

Table 1 presents a more detailed account of the top 10 academic institutions by which indexed papers were submitted, with the University Of Michigan, University of Groningen and University of Illinois as the top most productive institutions. The data show that the corresponding ratios for the institutions in the Netherlands and England are much greater than those in the USA, indicating that the institutions in their respective countries dominate the academic research in the ABM field.

Table 2 provides the top 10 subject areas in which ABM was most widely studied. The most highly ranked subject area was social science interdisciplinary studies, with approximately 17% of total, followed by economics and computer science interdisciplinary applications related to ABM.

Table 3 shows the 10 articles yielding the most citations. The results reveal that Lambin, Geist, and Lepers (2003) is an icon in ABM [33] which is the most influential paper, while Snijders, van de Bunt, and Steglich (2010) owns the highest average citations per year, indicating that it has potential influences in the future [34].

Fig 4. The annual citations of the published papers (Source: Web of Science)

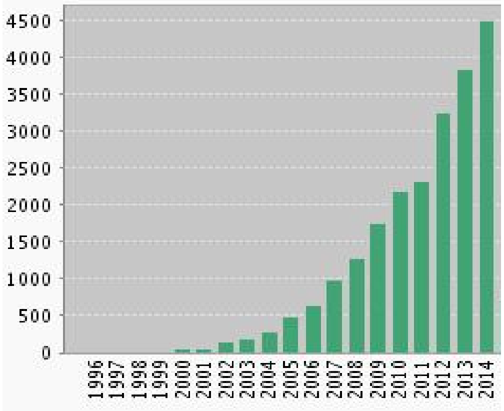


Fig 5. The top 10 most productive countries with regard to publication

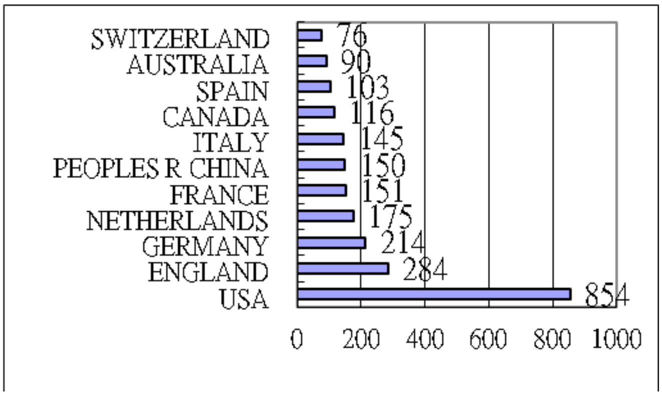


Table 1. Top 10 most productive institutes for publications related to ABM.

Rank	Institution Name	Count	%	Country	CC%
1	Univ. Michigan	67	2.63%	USA	7.85%
2	Univ. Illinois	35	1.37%	USA	20.00%
3	Univ. Groningen	34	1.34%	Netherlands	3.98%
4	Arizona State Univ.	33	1.30%	USA	3.86%
5	Univ. Penn	32	1.26%	USA	3.75%
6	Michigan State Univ.	31	1.22%	USA	3.63%
7	George Mason Univ.	28	1.10%	USA	3.28%
8	Harvard Univ.	28	1.10%	USA	3.28%
9	Carnegie Mellon Univ.	26	1.02%	USA	3.04%
10	UCL	26	1.02%	England	9.15%

*CC %: comprising % of the country

Table 2. Top 10 subject areas for articles related to ABM

Subject Area	Count	%
Social Sciences Interdisciplinary	401	15.74%
Economics	363	14.25%
Computer Science Interdisciplinary Applications	259	10.17%
Environmental Studies	224	8.80%
Mathematics Interdisciplinary Applications	213	8.36%
Operations Research Management Science	191	7.50%
Computer Science Artificial Intelligence	187	7.34%
Management	186	7.30%
Geography	163	6.40%
Environmental Sciences	152	5.97%
Multidisciplinary Sciences	134	5.26%

Table 3. The 10 most cited articles (data retrieved on March 28, 2014)

Articles	TC	ACPY
Dynamics of land-use and land-cover change in tropical regions[33]	496	38.15
Multi-agent systems for the simulation of land-use and land-cover change: A review[35]	461	35.46
Complexity theory and organization science[36]	357	21
From factors to actors: Computational sociology and agent-based modeling[37]	280	20
Introduction to stochastic actor-based models for network dynamics[34]	254	42.33
The evolution of strong reciprocity: cooperation in heterogeneous populations[38]	230	19.17
Using similarity criteria to make issue trade-offs in automated negotiations[39]	218	15.57
Cooperative multi-agent learning: The state of the art[40]	200	18.18
Balancing search and stability: Interdependencies among elements of organizational design[41]	187	14.38
Fission-Fusion Dynamics New Research Frameworks[42]	182	22.75

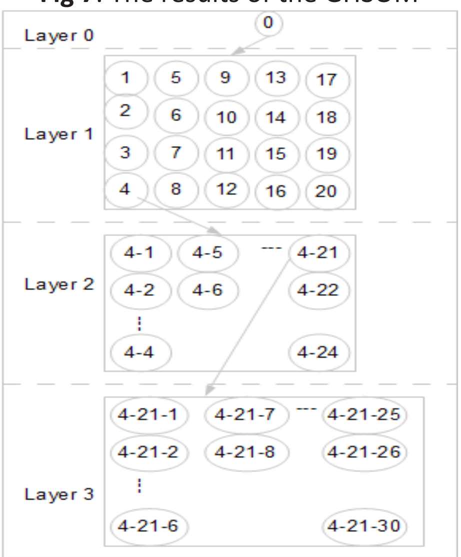
*TC: Times cited, ACPY: average citation per year

3.2 GHSOM and Topic Analysis

Through the process of applying the GHSOM to topic analysis, as displayed in Figure 2, we obtained the result, as displayed in Figure 7, in the clustering phase. The model comprised two layers and 83 nodes. All 2,547 articles were clustered into a SOM of 5 x 4 nodes in layer 1. The articles clustered into node 4 were further re-grouped into a SOM of 6 x 4 in layer 2, and node 4-21 was regrouped into a SOM 6 x 5 in layer 3.

In the interpreting phase, for each node of the GHSOM, we count the df_i value of each key term in all articles, cluster them into a particular node and assigned a key term with the highest df_i value (or several key terms if their df_i values were very close) as the topic category. The results are presented in Figures 9, 10, and 11; the number in parentheses refers to the number of clustered articles. For instance, there were 64 articles clustered into node 1, and on the basis of the interpretation of the topic category, this node was named the "management self-organized criticality thermodynamics" node. Node 4, denoted as '*', was multi-disciplinary and multi-conceptual and, thus, was re-grouped into more topics in Figure 9. Specially, node 4-2 in Figure 9 has no specific topic, which means that there was no highest df_i term in this node. Node 4-21, denoted as '**', was also further re-grouped into the more detailed topics of layer 3 in Figure 10.

Fig 7. The results of the GHSOM



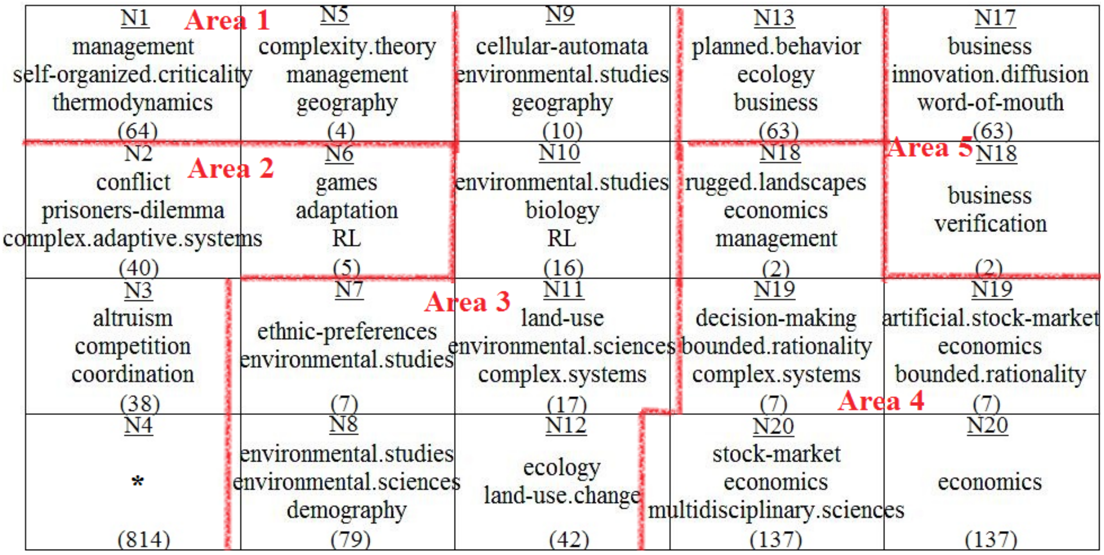


Fig 8. First-layer interpretation results of the GHSOM. Reinforcement learning is denoted as RL.

On the basis of these dominant topical clusters in the collection of articles, further specific topics were obtained in layer 2 (Figure 9), and the articles in node 4 were further re-grouped into sub-category topics including “biology”, “small-world networks”, “social networks”, “sociology”, “games” and “urban studies”, and so on. For instance, node 4-1 is composed of sub-category topics including “biology”, “evolutionary games”, “group selection” and “strong reciprocity”. On the basis of the number of groups, Layer 2 could be categorized into five classes: Node 4-1 as biology, Area 4-1 as social network/small world networks, Area 4-2 as game theory, Area 4-3 as sociology, and Node 4-24 as urban studies.

The interpretation results for the second- and third-layers of the GHSOM shown in Figures 8, 9, and 10 were more delicate than those in Table 2. Another interesting observation found in Figures 8, 9, and 10 is that the two neighboring nodes are much more closely related than the remote nodes. For example, articles clustered in Area 1 (including nodes 1 and 5) related to the concept of “management” at the top-left corner of Figure 8 are obviously very different from those clustered in Area 3 (including nodes 7, 8, 9, 10, 11 and 12) related to the concept of “environmental studies” and “ecology” in the middle corner of Figure 8.

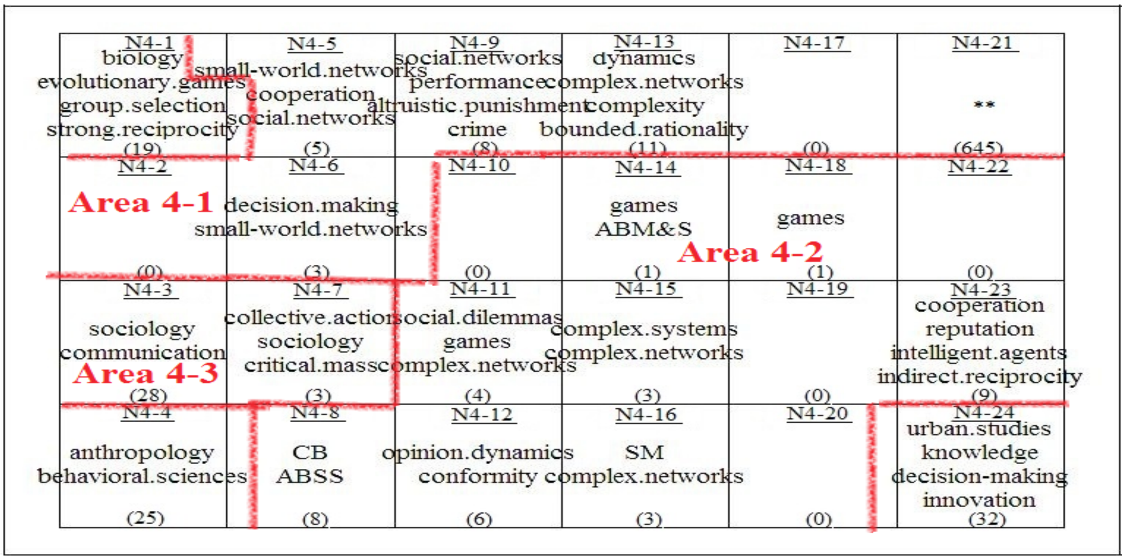


Fig. 9. The interpretation result of node 14 in the second layer. Collective behavior is represented by CB; agent-based social simulation is represented by ABSS; agent-based modeling and simulation is represented by ABM&S; statistical-mechanics is represented by SM.

4. DISCUSSION

In this paper, Tables 2 and 3 can explain why specific topics in certain subject areas cluster together according to the GHSOM results. Table 2 indicates the most productive subject areas using ABM, matching the keywords "economics" and "environment studies" spread throughout the topic analysis. More specifically, some works focus on land-use and land-cover change in environmental studies [33, 35], as presented in Table 3, may explain the clustering behavior mentioned above, because their articles were prominently cited in research related to the keywords "land-use" and "land-cover change". This implies that ABM provides many authors of social sciences a powerful tool for solve certain problems and explaining certain phenomena. Thus, the authors summarize in the table 4 from the results in Figure 8 and 9.

For area 2 and node 4-1 in Table 4, the studies about cooperation and evolution had a long research history because survival of the fittest fails to provide a biological explanation for selfless altruism from an evolutionary perspective [43]. Early scholars sought to discover how and why selflessness could have evolved. For instance, the biological explanation was expanded to the genetic kinship theory [44], reciprocal altruism [45], and group selection of sociobiology [46]. Since the late 1970s, political scientist Robert Axelrod from the University of Michigan has held three computer tournaments of iterated prisoners' dilemmas to study issues such as cooperation and altruism. He has created a new era by applying computer simulation to the study of altruism and cooperation [43, 47]. Since then, social scientists began to gradually apply ABM to sociology and political science, among other fields, using the evolutional game.

Table 4. The summary of the GHSOM results

Area	Subject Area	Associated topics	Main articles
area 1	management	self-organized criticality, thermodynamics, complexity theory	[34]
area 2	social science	conflict, game, prisoner's dilemma, altruism, competition	[38], [37]
area 3	environmental studies, ecology	land-use, land-use change, cellular-automata, etc.	[33], [35]
area 4	economics	stock market, bounded rationality, complex systems	[42], [48]
area 5	business	innovation diffusion, word-of-mouth	[11], [49]
node 4-1	biology	evolutionary games, group selection, strong reciprocity	[38]
area 4-1	small-world and social network	complex networks, bounded rationality, cooperation	[36], [37], [50]
area 4-2	game theory	complex networks, social dilemma, cooperation, reputation	[40]
area 4-3	sociology	communication, collective action, critical mass	[51]

For area 4-1, ABM also helps in building a virtual dynamic process model of utility maximizing social actors embedded within social networks. Actors make social choices under combinations of betrayal or cooperative rules. Thus, social scientists would observe the evolutionary macro-phenomena from micro-motives in the social network [37].

Spatial ABMs were primarily implemented in tools or platforms such as Netlogo or Repast, thus facilitating scholars in environmental studies, ecology, and geography to model and solve their problems using ABM. For example, the complexities of land-use and cover change by proposing a framework are highlighted for understanding tropical regions [33]. An overview of multi-agent system models of land-use and cover change is also presented [35].

Regarding the artificial stock market or the market in economics, ABM provides a good tool to study investors' behaviors. For example, the return series is independently and identically distributed (iid), hence supporting the efficient market hypothesis (EMH) [42]. And the artificial markets emerging form an agent-based social simulation where agents represent consumers, firms, or industries interacting under simulated market conditions, and as a result, they identified seven recommendations for guiding the development of artificial markets as a venue for technological innovation research [12].

In the past few decades, the number of published papers referencing ABM methodology has been growing because of advancements in and the ease of use of ABM simulation platforms such as SWARM of Santa Fe Institute, Starlogo of MIT, Netlogo of Northeastern University, and REPAST of the University of Chicago. ABM tools enable the scholars of subject areas such as social science/interdisciplinary studies, economics, management, mathematics/interdisciplinary applications and environmental studies to conduct research in natural and social sciences. A comprehensive survey of ABM platforms [52, 53]. Their goal is to help researchers select the toolkit that best suits their purposes.

Any researcher who has ever used ABM (such as NetLogo) would easily regard such a model as a simple version of a computer game. At first glance, the concept of ABM and computer simulation games (such as SimCity, The Sims, etc.) is somewhat similar, because both are based on the principle of a computer program as the agent and both allow the user to setup program agents' behaviors and parameters. In addition, both provide interaction with other computer program agents or environmental variables through one or more of these agents of variables on behalf of the user agent. However, ABM is not a simple computer game, and ABM researchers consider it best not to simulate a real world and not to focus on the programming training itself but rather to focus on theory, meaning that the researcher cooperates better with other scholars of other disciplines. Different from video games, ABM researchers will not completely participate in or intervene in the agents' interactions. The researcher is an observer and his/her role is akin to watching a video game demonstration (demo). More precisely, ABM is intentional computing [54]. ABM simulation is not interested in the stimulated sensory elements of the game but in providing the researchers the entire simulation experience and process, examining the results of the operation for the purpose of drawing a theoretical hypothesis. Therefore, the design of ABM emphasizes the internal validity of the program, meaning that research must focus on the assumptions behind the theory [55, 56].

5. CONCLUSION

This bibliometric study provides an overall picture of articles on ABM published in the SSCI database. We observed a steady growth in the number of papers related to ABM between the years of 1995 and 2014. The most productive countries are the USA, England, and Germany, while the most productive institutions are the University Michigan, the University of Groningen, and the University of Illinois. The study also shows that the variety of literature appeared to be scattered across a wide range of subject areas and that the main subject areas were primarily within the fields of social sciences interdisciplinary studies, economics, computer science interdisciplinary applications, and environmental studies. Lambin, Geist, and Lepers (2003) was the most influential authors with regard to the number of times cited [33].

The GHSOM tool has all of the benefits of SOM, providing a map from a higher dimensional input space to a lower dimensional map space and providing a global orientation of independently growing maps in the individual layers of the hierarchy, which facilitated navigation across the branches. The results of the GHSOM indicate the main topics related to the ABM researches of any specific country. Some interpretation presents topic analysis, indicating the relationship among different disciplines.

In this study, the GHSOM results support the suggestion of [10], although they perform a co-citation analysis to visualize the intellectual structure of social simulation and its development. The clusters include social networks and innovative diffusion, opinion dynamics, environmental aspects, behavioral economics and evolution and learning in social dilemmas. However, their dataset was limited to only the Journal of Artificial Societies and Social Simulation (JASSS) articles, while this study provided an overall analysis covering literature related to ABM from the SSCI database.

With respect to the future applications of ABM, this study illuminates some points from the GHSOM results. ABM provides scholars from ecology/environmental studies, economics, sociology, and business/management a convenient and powerful tool to address "how" or "what-if" questions, that is, observing how the complicated social phenomena in question has been formulated through the interaction between the simulated agents [57-59]. Unlike the focus of statistics and econometrics on the causal relationships between variables, ABM is mainly concerned with the replication of the computational model, which Wilensky and Rand (2007) argue may be even more beneficial to the scientific community than the replication of physical experiments for fostering a shared understanding of this particular model's modeling concepts and practices in the discussion of the actual replication of the scientific model [11]. In addition, the patterns being discovered through such observations may be used either to test existing theories or to explore new ones [60]. Axelrod [60] also suggests that ABM can be used to describe certain fundamental questions in many fields, thereby promoting inter-disciplinary cooperation. When existing mathematical methods fall short, ABM presents itself as a useful tool to reveal the underlying unity behind various academic fields.

REFERENCES

[1] Keller, E. F. 2005. "Marrying the Premodern to the Postmodern: Computers and organisms after World War II." In *Mechanical bodies, Computational minds: artificial intelligence from automata to cyborgs*, edited by Franchi, S. and Guzeldere, G., 203-228. Cambridge: MIT Press.

[2] Von Neumann, J., and Burks, A. W.,Essays on cellular automata. Edited by Burks, A. W.: University of Illinois Press, (1966). Original edition.

[3] Gardner, M., Mathematical games: The fantastic combinations of John Conway's new solitaire game 'Life'. *Scientific American,* 223 (4):120-123, (1970).

[4] Macal, C. M., and North, M. J., Tutorial on agent-based modelling and simulation. *Journal of Simulation,* 4 (3):151-162, (2010).

[5] Schelling, T. C., Dynamic Models of Segregation. *Journal of Mathematical Sociology,* 1 (2):143-186, (1971).

[6] Schelling, T. C.,Micromotives and Macrobehavior. New York: WW Norton, (1978). Original edition.

[7] Tesfatsion, L., Introduction to the special issue on agent-based computational economics. *Journal of Economic Dynamics and Control,* 25 (3-4):281-293, (2001).

[8] Tesfatsion, L., Agent-based computational economics: Growing economies from the bottom up. *Artificial life,* 8 (1):55-82, (2002).

[9] Macy, M.W., and Willer, R., From Factors to Actors: Computational Sociology and Agent-Based Modeling. *Annual review of sociology,* 28:143-167, (2002).

[10] Meyer, M., Lorscheid, I., and Troitzsch, K. G., The Development of Social Simulation as Reflected in the First Ten Years of JASSS: a Citation and Co-Citation Analysis. *Jasss-the Journal of Artificial Societies and Social Simulation,* 12 (4):A224-A243, (2009).

[11] Wilensky, Uri, and Rand, William. Making models match: Replicating an agent-based model. *Journal of Artificial Societies and Social Simulation,* 10 (4):2, (2007).

[12] Zenobla, B., Weber, C., and Daim, T., Artificial markets: A review and assessment of a new venue for innovation research. *Technovation,* 29 (5):338-350, (2009).

[13] Choi, D. G., Lee, Y. B., Jung, M. J., and Lee, H., National characteristics and competitiveness in MOT research: A comparative analysis of ten specialty journals, 2000-2009. *Technovation,* 32 (1):9-18, (2012).

[14] Lee, S., Yoon, B., and Park, Y., An approach to discovering new technology opportunities: Keyword-based patent map approach. *Technovation,* 29 (6-7):481-497, (2009).

[15] Cornelius, B., and Persson, O., Who's who in venture capital research. *Technovation,* 26 (2):142-150, (2006).

[16] Abramo, G., D'Angelo, C. A., Di Costa, F., and Solazzi, M., University-industry collaboration in Italy: A bibliometric examination. *Technovation,* 29 (6-7):498-507, (2009).

[17] Dittenbach, M, Rauber, A, and Merkl, D. Uncovering hierarchical structure in data using the growing hierarchical self-organizing map. *Neurocomputing,* 48 (1-4):199-216, (2002).
[18] Rauber, A, Merkl, D, and Dittenbach, M. The growing hierarchical self-organizing map: exploratory analysis of high-dimensional data. *IEEE Transactions on Neural Networks,* 13 (6):1331, (2002).
[19] Wolfram, D,Applied informetrics for information retrieval research: Greenwood Publishing Group, (2003). Original edition.
[20] Hassan, E. Simultaneous mapping of interactions between scientific and technological knowledge bases: the case of space communications. *Journal of the American Society for Information Science and Technology,* 54 (5):462-468, (2003).
[21] Chau, M, Huang, Z, Qin, J, Zhou, Y, and Chen, H. Building a scientific knowledge web portal: The NanoPort experience. *Decision Support Systems,* 42 (2):1216-1238, (2006).
[22] Grupp, H, and Schmoch, U, eds. 1992. *Perception of scientification as measured by referencing between patents and papers*. Edited by Grupp, H, *Dynamics of Science-Based Innovation*. Heidelberg: Spring Verlag.
[23] Noyons, E., Bibliometric mapping of science in a policy context. *Scientometrics,* 50 (1):83-98, (2001).
[24] Noyons, ECM, and van Raan, AFJ. Monitoring scientific developments from a dynamic perspective: self-organized structuring to map neural network research. *Journal of the American Society for Information Science,* 49 (1):68-81, (1998).
[25] Ding, Y, Chowdhury, GG, and Foo, S. Bibliometric cartography of information retrieval research by using co-word analysis. *Information Processing & Management,* 37 (6):817-842, (2001).
[26] Shih, JY, Chang, YJ, and Chen, WH. Using GHSOM to construct legal maps for Taiwan's securities and futures markets. *Expert Systems with Applications,* 34 (2):850-858, (2008).
[27] Li, S. T., and Chang, W.C. Design And Evaluation Of A Layered Thematic Knowledge Map System. *Journal of Computer Information Systems,* 49 (2)(2009).
[28] Campanario, JM. Using neural networks to study networks of scientific journals. *Scientometrics,* 33 (1):23-40, (1995).
[29] Kohonen, T. Self-organized formation of topologically correct feature maps. *Biological cybernetics,* 43 (1):59-69, (1982).
[30] Kohonen, T, Kaski, S, Lagus, K, Salojarvi, J, Honkela, J, Paatero, V, and Saarela, A. Self organization of a massive document collection. *IEEE Transactions on Neural Networks,* 11 (3):574-585, (2000).
[31] Tsaih, RH, Lin, WY, and Huang, SY. Exploring Fraudulent Financial Reporting with GHSOM. *Intelligence and Security Informatics*:31-41, (2009).
[32] Salton, G.,Automatic text processing: the transformation, analysis, and retrieval of information by computer. Reading, MA: Addison-Wesley, (1989). Original edition.
[33] Lambin, E. F., Geist, H. J., and Lepers, E., Dynamics of land-use and land-cover change in tropical regions. *Annual Review of Environment and Resources,* 28:205-241, (2003).
[34] Snijders, T. A. B., van de Bunt, G. G., and Steglich, C. E. G., Introduction to stochastic actor-based models for network dynamics. *Social Networks,* 32 (1):44-60, (2010).
[35] Parker, D. C., Manson, S. M., Janssen, M. A., Hoffmann, M. J., and Deadman, P., Multi-agent systems for the simulation of land-use and land-cover change: A review. *Annals of the Association of American Geographers,* 93 (2):314-337, (2003).
[36] Anderson, P., Complexity theory and organization science. *Organization Science,* 10 (3):216-232, (1999).
[37] Macy, M. W., and Willer, R., From factors to actors: Computational sociology and agent-based modeling. *Annual Review of Sociology,* 28:143-166, (2002).
[38] Bowles, S., and Gintis, H., The evolution of strong reciprocity: cooperation in heterogeneous populations. *Theoretical Population Biology,* 65 (1):17-28, (2004).
[39] Faratin, P., Sierra, C., and Jennings, N. R., Using similarity criteria to make issue trade-offs in automated negotiations. *Artificial Intelligence,* 142 (2):205-237, (2002).
[40] Panait, L., and Luke, S., Cooperative multi-agent learning: The state of the art. *Autonomous Agents and Multi-Agent Systems,* 11 (3):387-434, (2005).
[41] Rivkin, J. W., and Siggelkow, N., Balancing search and stability: Interdependencies among elements of organizational design. *Management Science,* 49 (3):290-311, (2003).
[42] Aureli, F., Schaffner, C. M., Boesch, C., Bearder, S. K., Call, J., Chapman, C. A., Connor, R., Di Fiore, A., Dunbar, R. I. M., Henzi, S. P., Holekamp, K., Korstjens, A. H., Layton, R., Lee, P., Lehmann, J., Manson, J. H., Ramos-Fernandez, G., Strier, K. B., and Van Schaik, C. P., Fission-Fusion Dynamics New Research Frameworks. *Current Anthropology,* 49 (4):627-654, (2008).
[43] Dawkins, R.,The selfish gene. New York, USA: Oxford University Press, (2006). Original edition.
[44] Hamilton, W. D., The genetical theory of social behaviour, I, II. *Journal of Theoretical Biology,* 7 (1):17-52, (1964).
[45] Trivers, R. L., Evolution of Reciprocal Altruism. *Quarterly Review of Biology,* 46 (1):35-57, (1971).
[46] Wilson, E. O., Sociobiology: the new synthesis. *Traduccion castellana,* (1975).
[47] Hoffmann, R., Twenty years on: The evolution of cooperation revisited. *Journal of Artificial Societies and Social Simulation,* 3 (2):1390–1396, (2000).

[48] Cochocki, A, and Unbehauen, Rolf,Neural networks for optimization and signal processing: John Wiley & Sons, Inc., (1993). Original edition.
[49] Delre, S. A., Jager, W., Bijmolt, T. H. A., and Janssen, M. A., Targeting and timing promotional activities: An agent-based model for the takeoff of new products. *Journal of Business Research,* 60 (8):826-835, (2007).
[50] Barbesino, P., Towards a post-foundational understanding of community. *Kybernetes,* 26 (6-7):689-702, (1997).
[51] Bhattacharyya, S., and Ohlsson, S., Social creativity as a function of agent cognition and network properties: A computer model. *Social Networks,* 32 (4):263-278, (2010).
[52] Bandini, S., Manzoni, S., and Vizzari, G., Agent Based Modeling and Simulation: An Informatics Perspective. *Jasss-the Journal of Artificial Societies and Social Simulation,* 12 (4):A51-A66, (2009).
[53] Nikolai, C., and Madey, G., Tools of the Trade: A Survey of Various Agent Based Modeling Platforms. *Jasss-the Journal of Artificial Societies and Social Simulation,* 12 (2)(2009).
[54] David, N., Sichman, J.S., and Coelho, H., The logic of the method of agent-based simulation in the social sciences: Empirical and intentional adequacy of computer programs. *Journal of Artificial Societies and Social Simulation,* 8 (4)(2005).
[55] Becker, J., Niehaves, B., and Klose, K., A framework for epistemological perspectives on simulation. *Journal of Artificial Societies and Social Simulation,* 8 (4)(2005).
[56] Schmid, A., What is the Truth of Simulation? *Journal of Artificial Societies and Social Simulation,* 8 (4)(2005).
[57] Bui, T., and Lee, J., An agent-based framework for building decision support systems. *Decision Support Systems,* 25 (3):225-237, (1999).
[58] Epstein, J. M., Agent-based computational models and generative social science. *Complexity,* 4 (5):41-60, (1999).
[59] Epstein, J. M., and Axtell, R.,Growing artificial societies: MIT press Cambridge, MA, (1996). Original edition.
[60] Axelrod, R. 2006. "Agent-based modeling as a bridge between disciplines." In *Handbook of Computational Economics*, edited by Tesfatsion, L. and Judd, K. L., 1565-1584. Elsevier.

AUTHOR'S BIOGRAPHY

Dr. Chen-Wo Kuo is the Section Chief of Department of Education, Exhibition and Information Service in National Palace Museum, Taipei. He is also an adjunct professor which teaches the classes about the digital archives and designs in the National Taiwan University of Arts. With the experiences in dedicating the new media arts exhibitions for National Palace Museum and winning appraises from professionals and visitors, he mainly focuses in exploring the new technologies in new media arts field.

Dr. Yu-Hsiang Yang is currently a post-doctoral researcher in National Palace Museum, Taipei, Taiwan. He earned a Ph.D degree in information systems from National Chengchi University. Herewith the interests of big data analysis and text mining in the museum, he has focused his research that tightly associated with the new media arts using information technologies.

Citation: Chen-Wo Kuo and Yu-Hsiang Yang (2015) The Application Trends of the Agent-Based Modeling Literature. IJHSSE 2(4), pp: 199-210.