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Exploring emerging trends in agent-based modeling using bibliometric analysis and growing hierarchical self-organizing maps

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Abstract: Agent-based modeling (ABM) refers to the computer simulation of agents in a dynamic system. The underlying problem of ABM was first theorized by John von Neumann in 1940. However, research did not address this problem until the concept of ABM emerged in this decade. This study highlights emerging trends in international literature related to ABM for articles in the Social Science Citation Index (SSCI) database published since 1995. Because of the lack of a state-of-the-art method to identify emerging technologies, we employed the bibliometric technique and a growing hierarchical self-organizing map (GHSOM) to explore the emerging trend of ABM.

Firstly, this paper reviews ABM methodology and state-of-the-art research methods, namely the bibliometric technique and GHSOMs. Secondly, we explain the research data and method. The dataset used in this study was derived from the SSCI database of the Web of Science. An empirical search command was used to retrieve data related to ABM and then a bibliometric analysis was performed on the ingested data. The results revealed that ABM does emerge and development related to ABM continued to expand. We then deployed the application of the GHSOM to topic analysis in three phases: a data-preprocessing phase, -clustering phase, and -interpreting phase. The results indicated that the common topics related to ABM are complexity theory, the prisoner's dilemma, altruism, land-use change, cellular automata and innovation diffusion etc. This paper illustrates the potential of using GHSOM to explore the applications of emerging technologies. The study is the first of its kind thus far.

Keywords: Emerging Technology, Agent-Based Modeling (ABM), Growing Hierarchical Self-Organizing Map (GHSOM), Informetrics, Bibliometrics, Scientometrics

1. Introduction

Agent-based modeling (ABM), or the multiagent system, refers to the computer simulation of agents (representing individual roles) in a dynamic system. Here, agents are different representatives who interact with each other or with the environment on the basis of pre-established rules. An 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 combined with 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 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 processes 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 provide local information using a grid or lattice environment [4]. Relevant research was not undertaken until the term ABM emerged. We are interested in the development process of ABM, under what circumstances it emerges, and its application areas. Therefore, the first objective of this research is to explore the emerging trend of ABM.

Currently, no proper method identifies or proves the emergence of such technologies. Therefore, we apply research methods from the field of bibliometric study to explore and illustrate the emerging trend of ABM. Furthermore, no research has explored the application areas of emerging technologies. We propose to employ an unsupervised learning method—a growing hierarchical self-organizing map (GHSOM)—with coword analysis to discover the application topic map of ABM. The second objective of this study is to reveal the major topics or conceptual interrelations of literature related to ABM. To reveal the annual major topics and conceptual interrelations of articles related to ABM, we adopted GHSOM to cluster the conceptual topics into a hierarchical representation of dynamic 2-dimensional interrelated structures within the data

1.1 State-of-the-Art ABM

Derived from the Schelling segregation model [5], ABM begins with rules of behavior for individuals and uses simulation to discover the large-scale implications of these rules. Thomas Schelling, winner of the 2005 Nobel Memorial Prize in Economic Sciences (shared with Robert Aumann), called this micromotives and macrobehavior [6]. To understand particular phenomena, ABM has been applied in almost every field—including multiple scientific disciplines, such as economics, physics, biology, and ecology, for exploring complex adaptive systems. For instance, an economic system in agent-based economics can be composed of heterogeneous agents, and summation variables are the results of interactions between these heterogeneous agents. Unlike traditional macroeconomics, which employs the top-down mode of thinking, ABM has introduced a bottom-up style of thinking to macroeconomics under a new paradigm, one which presents a challenge to most economists [7]. Thus, ABM is an ideal tool to advance thinking from the micro to the macro perspective and to observe the relationships between these two levels [8].

ABM substantially illustrates the special relation between economics and physics [9]. For example, Schelling's work [5, 6], which demonstrated how slight differences in micromotives among heterogenous agents lead to impressive macro behaviors. Schelling wanted to falsify the standard view of segregation between black and white communities in the United States, which assumed strong differences in preferences to explain the observed concentrations. By using manually implemented ABM on a check board, the author showed that tiny variations in tastes are sufficient to lead to macroscopic segregation when allowing the system to evolve over sufficiently long periods. Small microeffects lead to large macroconsequences. This discovery was a breakthrough in the social sciences and changed the perspective on community segregation. To a physicist trained in the field of phase transitions and statistical physics, this result is clear: tiny differences in the interactions between pairs of molecules (oil–oil, water–water, and oil–water) renormalize into macroscopic demixing [9]. This is a significant example of the effect of repeated interactions leading to large-scale collective patterns. In addition to energy, entropy is a crucial and often chief contribution to large-scale pattern formation, and this understanding requires the typical statistical physics training that economists and social scientists often lack [9].

The term ABM is often bundled with the term complex system [9–11]. The application of complexity theory and its major tool ABM is still relatively recent, which can be largely summarized in three threads [10]. The first is the thread of individual-based modeling (IBM) in ecology. This line of research was initiated in the 1970s and advanced in the 1980s, characterized by relatively "pure" ecological studies contributing to later complex system-related ABM development. Although IBM and ABM are considered largely equivalent, some features differentiate one from the other. Although IBM focuses more on the role of heterogeneity and uniqueness of individuals, ABM, with substantial contribution from computer science and social sciences, provides more attention to the decision-making process of agents and their contextual social organizations [12].

The second thread of ABM use in complex systems is characterized by conceptual or theoretical tests in social science fields (e.g., thought experiments). Work under this domain has become popular, including the segregation models of Schelling [5], the prisoners' dilemma for testing cooperative strategies, emergence from social life simulations (e.g., SugarScape model; [13]), and social generative research in complex adaptive systems [14, 15]. Such efforts, usually made in virtual environments, feature ad hoc rules used to test "what if" scenarios or explore emergent patterns. Efforts have also been made to answer archaeological questions using ABM, such as how or why certain prehistoric or ancient people abandoned settlements or adapted to changing environmental conditions [16]. Such efforts, closely related to explorations in game theory and complex adaptive systems, are precursors of modeling empirical complex systems.

The third and final thread involves applying ABM to realistic complex systems based on empirical data, which is usually coupled with cellular models (e.g., cellular automata) to spatially represent the environment. Considerable recent work has been devoted to the advancement of complexity theory and related ABM applications (e.g., [17, 18]). In addition, research on cellular automata and urban development contributes to complexity theory [19, 20].

Several major advantages of ABM have made it powerful in modeling complex systems. First, ABM has a unique power to model individual decision making while incorporating heterogeneity, and interaction or feedback [21]. A range of behavior theories or models, such as econometric models and bounded rationality theory, can be used to model human decisions and subsequent actions. Second, ABM can incorporate social and ecological processes, structure, norms, and institutional factors (e.g., [22]). Agents can be created to carry or implement these features, making it possible to "[put] people into place (local social and spatial context)" [23]. This complements current geographic information system functionality, focusing on representing form (i.e., "how the world looks"), rather than process (i.e., "how it works;" [24]). This advantage makes it technically smooth to couple human and natural systems in an ABM.

A complex system, similar to the social–ecological systems discussed by Ostrom [25], may have many human and nonhuman processes operating at multiple tiers that are hierarchically nested [26]. Research for understanding such processes from various disciplines have generated considerable findings. However, "without a common framework to organize findings, isolated knowledge does not cumulate" [26], preventing researchers from effectively addressing the aforementioned complexity. ABM has the flexibility to incorporate multiscale and multidisciplinary knowledge, to "co-ordinate a range of qualitative and quantitative approaches" [27], and mobilize the simulated world [28, 29]. Consequently, ABM is believed to have the potential to facilitate methodologically defensible comparisons across case study sites. For instance, ABM was used to synthesize several key studies of frontier land-use change worldwide [30].

ABM originates from a computer science paradigm called object-oriented programming [11], which has become popular since the 1980s with the advent of fast computers and rapid advancements in computer science. This paradigm "groups operations and data (or behavior and state) into modular units called objects," and allows the user organize objects into a structured network. Each object carries its own attributes (data) and actions (methods) with a separation between interface and implementation (technical details). The "implementation" feature makes the system work, whereas the user-friendly interface running above the system details "provides simple data input, output, and display functions so that other objects (or users) can call or use them" [29].

The ABM literature has developed vigorously in the last decade because of the convenience and advancements of ABM tools. Meyer et al. [31], for example, used a cocitation method to review social simulation, whereas Zenobla et al. [32] analyzed the strengths, weaknesses, opportunities, and threats of artificial markets. No overall analysis of ABM has yet been conducted, despite a plethora of research successfully applying bibliometric analysis to a number of multidisciplinary fields, such as technology management [33], technology creation [34], venture capital [35], and university–industry collaboration [36].

The ABM approach has benefited from the contributions of numerous other disciplines. A significant example is artificial intelligence research, in which multiple heterogeneous agents are coordinated to solve planning problems [12]. Also contributing to ABM development is artificial life research, which explores "life as it might be rather than life as it is" [37].

1.2 State-of-the-Art: Bibliometric Analysis and GHSOM

Chiang et al. [38] investigated the publishing trends of e-learning literature catalogued in the Social Sciences Citation Index (SSCI) database between 1967 and 2009. The findings indicate that (1) the quantity of research on e-learning is expanding remarkably, (2) the frequency indexes of authors' productivity do not appear to abide by Lotca's Law, (3) most research papers on e-learning are generated by multiple authorship, and (4) major e-learning applications are in research in areas, such as education, information science, library science, and computer science, or in interdisciplinary research. Finally, future directions of research on e-learning can be considered. Moreover, the data match Bradford's Law. The results reveal the potential to adopt bibliometric analysis in exploring emerging technologies.

This study assessed how ABM affects science and technologies as an emerging technological innovation tool. The SSCI database was searched for papers related to ABM published between 1995 and 2016. To elucidate ABM application trends, ABM-based technological trends and forecasts were investigated through bibliometric reviews of the literature in the SSCI database published since 1995. Standard bibliometric indicators, namely number of papers, number of authors, productivity by country, institutional collaboration, and most-cited articles, were analyzed.

deSolla Price suggested the dynamic mapping of science using scientific methods in the mid-1960s [39, 40]. Since then, research in bibliometrics and scientometrics has developed techniques to analyze publication data sets. It is quite desirable and valuable to cluster the major topics of a large collection of documents based on their content and to provide a topic landscape of the field. Such studies have applied bibliometric maps using coword analysis to visualize the cognitive structure of scientific knowledge bases and their interrelations [41–47].

In the data-preprocessing phase of text analysis, key terms, such as titles, keywords, and subject categories, represent the content of documents. Key terms describing the articles are extracted directly from the documents without manual intervention. These key terms are weighted according to a *tf* x *idf* weighting scheme [48–55]. Nevertheless, the difficulty is in further grouping or clustering the terms into a topic map on top of the *tf x idf* weighting.

The modern technique of natural language processing, namely sentiment analysis or opinion mining, is facing the same grouping difficulty. Sentiment analysis is becoming popular in various fields and is effective in prediction tasks [48, 56]. Nevertheless, most works using sentiment analysis focus on the classification of sentiment features by drawing on supervised learning, after the manual construction of topic map [48, 56]. To solve this problem, we developed a novel hybrid sentiment analysis in two phases: (1) extraction of text features regarding unsupervised learning, and (2) classification of the features regarding supervised learning and visualization of the results [48, 49, 51, 56]. For this method, we calculated the *tf x idf* indexes after the term extraction through data preprocessing and used K-means clustering and a self-organizing map (SOM; [57, 58]) to set up the topic model. Although the extraction through SOM provide slightly better results than did extraction through K-means, both methods are insufficient because they unevenly cluster the terms into one centralized topic [48, 49, 56].

Noyons and van Raan adopted the SOM technique to apply a coword approach to the science mapping, namely the organization of science. To overcome the deficit of SOM, GHSOM [41, 54, 59] refers to a layered thematic knowledge-map with key terms clustering as an updated version of SOM. The hierarchies and dynamic 2-dimensional architecture of maps is one of its largest improvements of SOM in the utilization of the GHSOM. It enables us to visualize the hierarchical topic maps and therefore can be used as a concept-representation to explore research topics in the literatures of ABM.

To reveal the major topics of articles related to ABM, this study employed the GHSOM approach to cluster the conceptual topics into a hierarchical representation of dynamic two-dimensional interrelated structures within the data. Through topic analysis of the ABM literature, this study also identified trends in ABM application. This is the first study of its type among existing research.

2. Dataset and Method

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

The first step was to set up and then use the searching schemata. An empirical search command was used to retrieve data related to ABM: “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).” The documents specifically included were articles and reviews. Book reviews, papers of the proceedings, letters, notes, and meeting abstracts were not considered. A total of 1,394 papers published between 1997 and 2011 were identified.

This study applied coword analysis using a GHSOM to cluster the primary topics of a large collection of documents related to ABM and reveal the topical landscape of the field. As with cocitation analysis, coword analysis has been used to determine the strength of relationships among textual containers, whether the containers are full-text documents or their surrogates, fields within documents (e.g., titles, descriptors), or queries submitted to information-retrieval systems. Techniques used for the analysis of word co-occurrence are similar to those used for cocitation analysis, consisting of cluster analyses and multidimensional scaling methods [53].

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A co-occurrence analysis of document content is usually performed using substantive keywords appearing in a bibliographic database record field such as the title, descriptors, or abstract. These fields encapsulate the topic of a document, although keywords from the body of the text can also be used [53]. The benefits of coword analysis are dependent on the application; the method can indicate the topical landscape of a field and cluster major topics in a large collection of documents based on their content. Many studies [42–47] have employed informetric maps using coword analysis to visualize the cognitive structures of scientific topics and the relationships that link them.

Coword analysis integrates many different methods to identify clusters of word co-occurrence. For this study, the GHSOM, which has been used successfully in comparable studies, was employed to identify distinct clusters of papers [52, 60].

The self-organizing map (SOM) was designed to apply the concept of unsupervised artificial neural networks in the processing of high-dimensional data and enable result visualization [41, 47, 57, 58, 61]. However, construction of an SOM requires a predefined number of nodes (neural processing units) and a static architecture. The nodes result in a representation of hierarchical relationships with limited capability. The GHSOM approach was developed to overcome these limitations; thus it is often applied in the field of information extraction [41, 52, 54, 59, 60, 62] . The GHSOM is based on the characteristics of an SOM but can automatically grow its own multilayer hierarchical structure in which each layer encompasses a number of SOMs, as shown in Figure 1.

The application of 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.

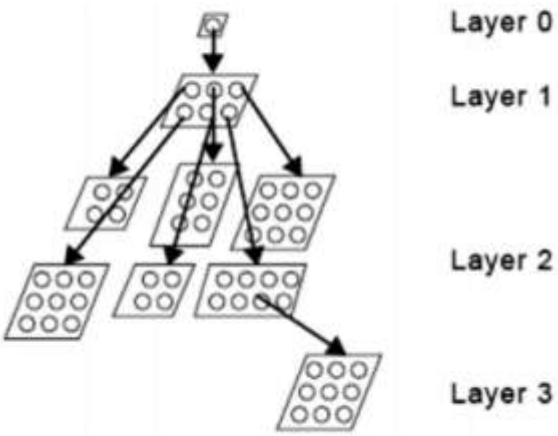

Figure 1. Structure of the GHSOM [54].

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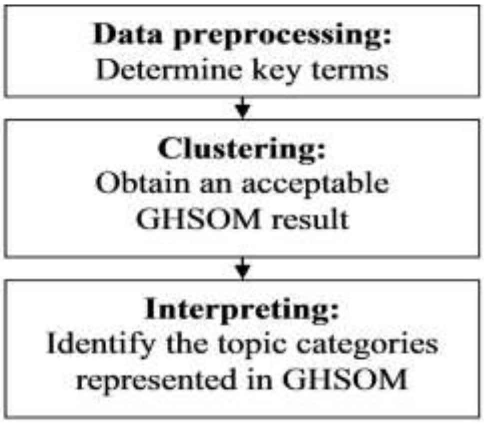

Figure 2. Three phases of topic analysis.

In the data-preprocessing phase, key terms, such as titles, keywords, and subject categories, represent the content of documents. Key terms describing the articles are extracted directly from the documents without manual intervention. These key terms are weighted according to a *tf* x *idf* weighting scheme [50–55]:

$$\boldsymbol{w_i(d) = tf_i(d) \times \log (N/df_i)} \qquad \textbf{(1)}$$

where $w_i(d)$ 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 weight of a term is always greater than or equal to zero. This weighting scheme assigns high values to terms considered essential for describing the content of a document or discriminating between various documents. A high weight is earned by terms with frequent appearances in a given document and infrequent appearances within the entire collection of documents. In this manner, weight assignment filters out commonly used terms. The top-order distinct key terms for document representation were selected [53, 55]. The resulting key-term vectors were used for GHSOM training.

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

In the interpreting phase, for each node of the GHSOM in the first layer and some nodes of the second layer that were regrouped into layer 3, the df_i of each key term in all articles was counted, the key terms were clustered into a particular node, and the key term with the highest df_i (or several key terms if their df_i values were similar) was defined as the topic category. Key terms were then automatically assigned by the GHSOM using the *tf* x *idf* weighting scheme.

3. Results of Informetric Analysis and the GHSOM

3.1 Overview of Productivity

A total of 1,394 papers related to ABM were retrieved from the SSCI database. Figure 3 plots the number of papers on the topic of ABM published between 1995 and 2011. According to the numerical data, numerous

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research papers published between 2009 and 2011 were cataloged in the SSCI database, with 186 (13.34% of all papers identified), 235 (16.86%), and 267 (19.15%) papers identified for the years 2009, 2010, and 2011, respectively. A trend of growth in these numbers began in 2004. Figure 4 shows the number of times the published papers related to ABM were cited for each year. The data suggest that the number of citations of these papers is also increasing. ABM has emerged and received considerable attention from researchers.

Figure 5 illustrates the 10 countries ranked as the top publishers of ABM-related papers in the SSCI database. The United States was the dominant country, followed by England and Germany.

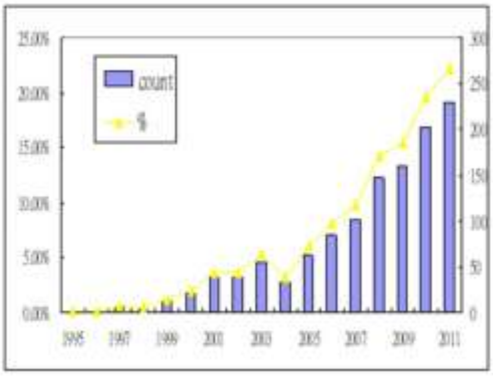

Figure 3. Number of papers published from 1995 to 2011.

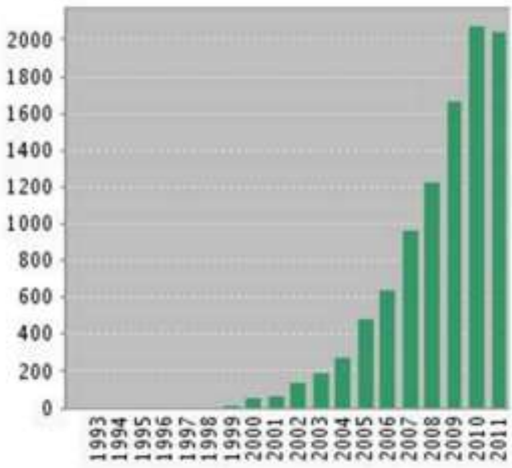

Figure 4. Annual citations of the published papers (Source: Web of Science).

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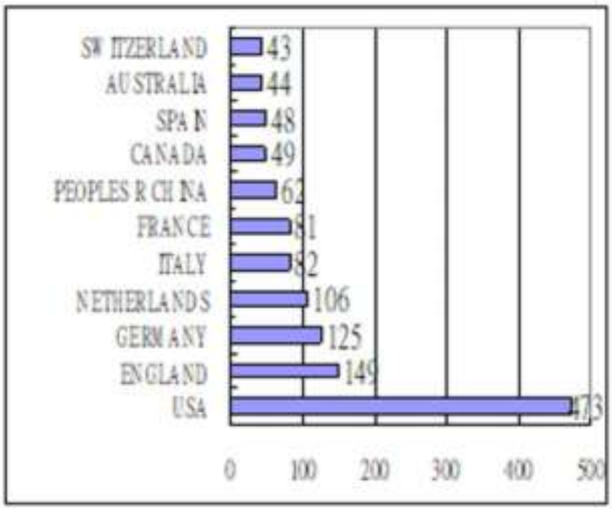

Figure 5. Ten most productive countries with regard to publication.

Table 1 presents a detailed account of the 10 academic institutions from which the most indexed papers were submitted, with the University of Michigan, University of Groningen, and University of Illinois the most productive institutions. The data show that the corresponding percentages of their country's output for institutions in the Netherlands and England were much higher than those for institutions in the United States, indicating that these institutions dominate academic research in the ABM field in their country. Table 2 lists the 10 subject areas in which ABM was most widely employed. The highest-ranked subject area was social science (interdisciplinary), with approximately 17% of the total, followed by economics and computer science (interdisciplinary).

Table 3 shows the 10 ABM-related articles that have obtained the most citations. Lambin et al. [63] is the most influential paper in the ABM literature, with the most overall citations and average citations per year.

Table 1. Ten most productive institutions for publications related to ABM.

Rank	Institution Name	Count	%	Country	% of country
1	Univ. Michigan	34	2.44%	USA	7.19%
2	Univ. Groningen	26	1.87%	Netherlands	24.53%
3	Univ. Illinois	26	1.87%	USA	5.50%
4	Harvard Univ.	20	1.44%	USA	4.23%
5	Univ. Penn	20	1.44%	USA	4.23%
6	Michigan State Univ.	18	1.29%	USA	3.81%
7	Arizona State Univ.	17	1.22%	USA	3.59%
8	George Mason Univ.	16	1.15%	USA	3.38%
9	Indiana Univ.	13	0.93%	USA	2.75%
10	UCL	13	0.93%	England	8.72%

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

Subject Area	Count	%
Social Science Interdisciplinary Studies	249	17.86%
Economics	187	13.42%
Computer Science Interdisciplinary Applications	123	8.82%
Environmental Studies	123	8.82%
Mathematics Interdisciplinary Applications	119	8.54%
Computer Science Artificial Intelligence	118	8.47%
Operations Research Management Science	116	8.32%
Management	109	7.82%
Computer Science Information Systems	88	6.31%
Geography	83	5.95%
Social Sciences Mathematical Methods	76	5.45%

Table 3. Ten most-cited articles (data retrieved on April 13, 2012).

Articles	TC1	ACPY2
Lambin et al. [63] Dynamics of land-use and land-cover change in tropical regions	303	30.3
Parker et al. [64] Multi-agent systems for the simulation of land-use and land-cover change: A review	284	28.4
Anderson [65] Complexity theory and organization science	256	18.3
Macy and Willer [66] From factors to actors: Computational sociology and agent-based modeling	184	16.7
Faratin et al. [67]) Using similarity criteria to make issue trade-offs in automated negotiations	165	15
Bowles and Gintis [68] The evolution of strong reciprocity: cooperation in heterogeneous populations	159	17.7
Rivkin and Siggelkow [69] Balancing search and stability: Interdependencies among elements of organizational design	126	12.6
Bunn [70] Forecasting loads and prices in competitive power markets	125	9.6
Panait and Luke [71] Cooperative multi-agent learning: The state of the art	114	14.3
Bower and Bunn [72] Model-based comparisons of pool and bilateral markets for electricity	106	8.2

[1]TC: times cited; [2]ACPY: average citations per year

3.2 GHSOM and Topic Analysis

Through the application of the GHSOM to topic analysis, as displayed in Figure 2, the result displayed in Figure 6 was obtained in the clustering phase. The model comprises two layers and 83 nodes. All 1,394 articles were clustered into an SOM of 5 x 4 nodes in layer 1. The articles clustered into node 4 were regrouped into an SOM of 6 x 4 nodes in layer 2, and node 4-21 was regrouped into an SOM of 6 x 5 nodes in layer 3.

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In the interpreting phase, for each node of the GHSOM, the df_i of each key term in all articles was counted, the key terms were clustered into a particular node, and the key term with the highest df_i (or several key terms if their df_i values were similar) was defined as the topic category. The results are presented in Figures 7–9; the numbers in parentheses in the figures refer to the number of clustered articles. For instance, 64 were articles clustered into node 1, and based on interpretation of topic categories, this node was named the "management–self-organized criticality–thermodynamics" node. Node 4 (denoted "*") was multidisciplinary and multiconceptual and, thus, is regrouped into more topics in Figure 7. Specifically, node 4-2 in Figure 8 has no specific topic, which means that there was no highest df_i value in this node. Node 4-21 (denoted "**") was also regrouped into the more detailed topics of layer 3, which are shown in Figure 9.

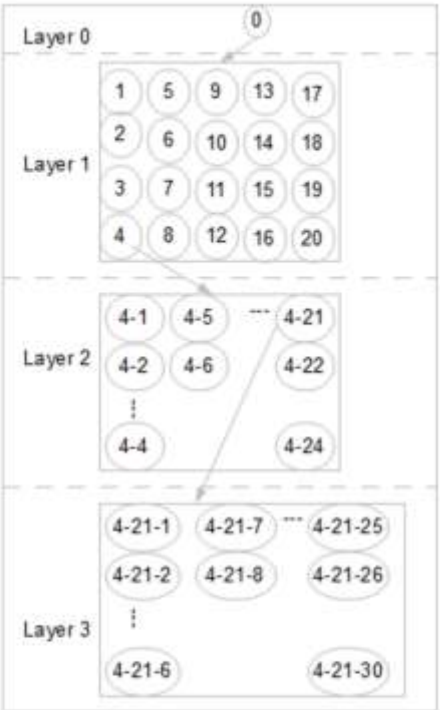

Figure 6. Result of the GHSOM.

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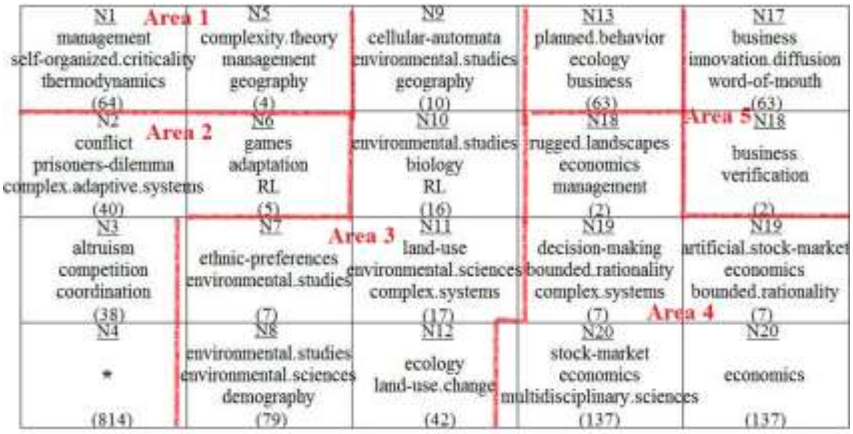

Figure 7. First-layer interpretation of the GHSOM. RL: Reinforcement Learning. [73]

On the basis of these dominant-topic clusters in the collection of articles, further specific topics were obtained in layer 2 (Figure 8), and the articles in node 4 were regrouped into subcategory topics including "biology," "small-world networks," "social networks," "sociology," "games," and "urban studies." For instance, node 4-1 is composed of subcategory topics including "biology," "evolutionary games," "group selection," and "strong reciprocity." Layer 2 was categorized into five classes: node 4-1 as biology, Area 4-1 as social networks or small-world networks, Area 4-2 as game theory, Area 4-3 as sociology, and node 4-24 as urban studies.

The interpretations of the second and third layers of the GHSOM (Figures 7–9) were more delicate than those shown in Table 2. In Figures 7–9, two neighboring nodes are much more closely related than two 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 very different from those clustered in Area 3 (including nodes 7–12) related to the concepts of "environmental studies" and "ecology" in the middle of Figure 7.

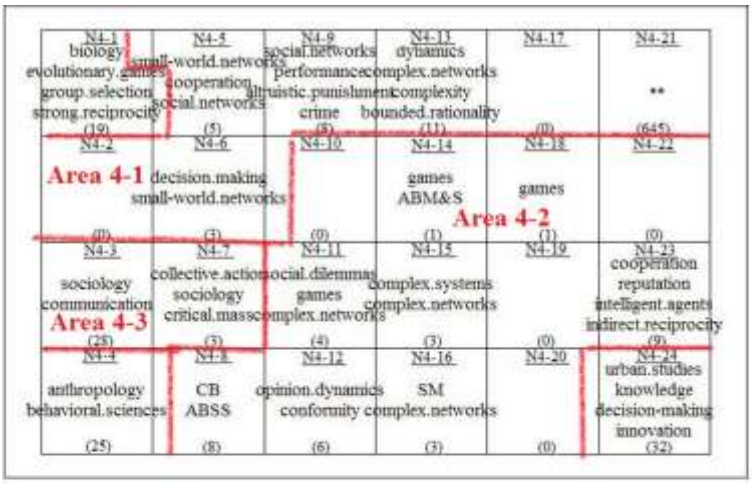

Figure 8. Interpretation of Node 14 in the second layer. CB: Collective Behavior; ABSS: Agent-Based Social Simulation; ABM&S: Agent-Based Modeling and Simulation; SM: Statistical Mechanics**.**

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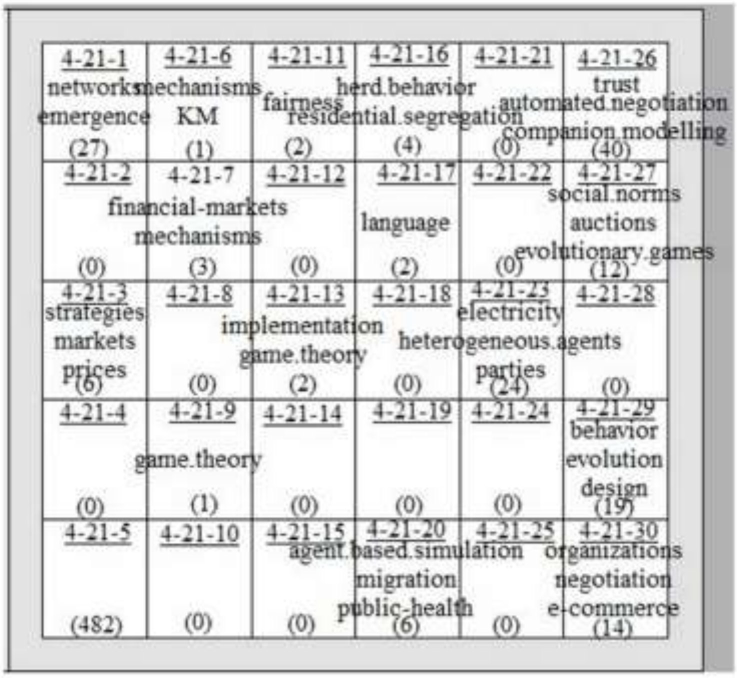

Figure 9. Interpretation of Node 4-21 in the second layer. KM: Knowledge Management.

4. Discussion

This discussion addresses the GHSOM results from two perspectives: information retrieval and content.

4.1 Information Retrieval

In this study, the *tf* × *idf* weights reflect the relative importance of words to a document within the collection. A subject keyword often has greater *tf* × *idf* weight than others because the subject area is the general direction of an article. Similar documents cluster together based on the specific importance of an individual word in the document, as indicated by the GHSOM. Therefore, subject area keywords have higher priority than other keywords. For example, the concept of "management" is prioritized over "self-organized criticality" in node 1 in Figure 8. The topic "complexity theory" precedes "management" in node 5.

This study assessed the differences and similarities in ABM research between disciplines for input keywords such as "complex systems" and "complexity theory." For instance, "complexity theory" is present in node 5 and "complex systems" is found in nodes 11 and 19; this indicates that articles use "complexity" to explain or apply concepts in their disciplines. Conversely, some words are discipline-specific; the terms are unique to a specific research area. For instance, "innovation diffusion" and "word-of-mouth" are specific to the business field.

The *tf* × *idf* weighting method measures the degree of correlation among documents and is often used to respond to user queries in search engines. Thus, its function can be identified in the document clustering performed for this study.

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4.2 Results of the GHSOM

Tables 2 and 3 explain why, according to the GHSOM results, specific topics in certain subject areas cluster together. Table 2 indicates the subject areas that employ ABM the most extensively; matching the keywords "economics" and "environment studies" spread throughout the topic analysis. More specifically, papers such as Lambin et al. [63] and Parker et al. [64], which focus on land-use and land-cover change in environmental studies (Table 3), may explain the clustering behavior because their articles are prominently cited in research related to "land-use" and "land-cover change." This implies that ABM is a powerful problem-solving and explanation tool for authors in science and technology fields.

Table 4. Summary of the GHSOM results

Area	Subject area	Associated topics	Main articles
Area 1	Management	Self-organized criticality, thermodynamics, complexity theory	Manson [74]
Area 2	Social science	Conflict, game, prisoner's dilemma, altruism, competition	Bowles and Gintis [68], Macy and Willer [66]
Area 3	Environmental studies, ecology	Land-use, land-use change, cellular-automata, etc.	Lambin et al. [63], Parker et al. [64]
Area 4	Economics	Stock market, bounded rationality, complex systems	Chen and Yeh [75], Raberto et al. [76]
Area 5	Business	Innovation diffusion, word-of-mouth	Windrum and Birchenhall [77], Delre et al. [78]
Node 4-1	Biology	Evolutionary games, group selection, strong reciprocity	Bowles and Gintis [68]
Area 4-1	Small-world and social network	Complex networks, bounded rationality, cooperation	Barbesino [79], Anderson [65], Macy and Willer [66]
area 4-2	Game theory	Complex networks, social dilemma, cooperation, reputation	Panait and Luke [71]
area 4-3	Sociology	communication, Collective action, critical mass	Bhattacharyya and Ohlsson [80]

Area 2 and node 4-1 contain key words related to cooperation and evolution, which have a long research history because survival of the fittest fails to provide a biological explanation for altruism from an evolutionary perspective [81]. Early scholars sought to discover how and why selflessness evolved. For instance, the biological explanation was expanded into genetic kinship theory [82], reciprocal altruism [83], and the group selection of sociobiology [84]. Since the late 1970s, political scientist Robert Axelrod from the

University of Michigan has held three computer tournaments of iterated prisoner's dilemmas to investigate cooperation and altruism. He started a new era of research by applying computer simulation to the study of altruism and cooperation [81, 85]. Since then, social scientists have begun to apply ABM to sociology and political science, among other fields, using evolution games.

Area 4-1 is related to social networks. ABM helps construct a virtual dynamic process model of utility-maximizing social actors embedded within social networks. Actors make social choices under combinations of competitive or cooperative rules. Thus, social scientists observe evolutionary macrophenomena from micromotives in the social network [66].

Spatial ABM has primarily been implemented in platforms such as NetLogo or Repast, helping environmental studies, ecology, and geography scholars to model and solve their problems. For example, Lambin et al. [63] highlighted the complexity of land-use and land-cover changes through a framework for understanding tropical regions. Parker et al. [64] presented an overview of multiagent system models of land-use and land-cover change.

ABM is additionally a favorable tool for investigating investor behavior in economic markets. For example, Chen and Yeh [75] demonstrated that the return series is independently and identically distributed, supporting the efficient market hypothesis. Zenobla et al. [32] reviewed the artificial markets emerging from an agent-based social simulation where agents represent consumers, firms, or industries interacting under simulated market conditions; on the basis of the results, they made seven recommendations for the development of artificial markets in technological innovation research.

In recent decades, the number of published papers referencing ABM methodology has grown because of advancements in the ease of use of ABM simulation platforms such as SWARM (Santa Fe Institute), Starlogo (Massachusetts Institute of Technology), NetLogo (Northeastern University), and Repast (University of Chicago). ABM tools enable scholars in subject areas such as social science, economics, management, mathematics, and environmental studies to conduct research. Bandini et al. [86] and Nikolai and Madey [87] have comprehensively surveyed ABM platforms to help researchers select the toolkit that best suits their purposes. Nikolai and Madey [87] also created a corresponding Wikipedia page comparing ABM software, with the comparison based on their research (http://en.wikipedia.org/wiki/ABM_Software_Comparison).

Heath, Hill, and Ciarallo [88] argued that most studies are either generators or mediators, depending on their level of understanding of the real systems on which a work is based. A generator is a simulation where little is known about the system of interest, and it primarily determines whether a given conceptual model or theory is capable of generating the observed behavior of the system. A mediator is a simulation wherein the system is moderately understood, and it primarily establishes the capability of the conceptual model to represent the system and provide insight into the system's characteristics and behaviors. According to Bandini et al. [86], a generator matches general-purpose frameworks whereas a mediator provides a higher level of linguistic support, thus reducing the distance between ABM and its implementation. Netlogo is one example of a generator, whereas the latest version of Repast is a mediator.

Any researcher who has used ABM (such as NetLogo) would consider an agent-based model a simple version of a computer game. At first glance, the concepts of ABM and computer-based simulation games (SimCity, The Sims, etc.) are somewhat similar because both are based on a computer program as the agent and both allow the user to program agents' behaviors and parameters. Additionally, both provide interaction with other computer-program agents or environmental variables through one or more of these agents or variables on behalf of the user. However, ABM is not a simple computer game, and ABM researchers prefer to not simulate the real world or focus on programming training, but rather prefer to focus on theory to allow the researcher to cooperate more efficiently with scholars of other disciplines. ABM researchers do not completely participate in the agents' interactions as they would in a video game. As an observer, the researcher's role is akin to watching a video-game demo. More precisely, ABM is intentional computing [89]. ABM is not interested in the sensory elements of the game but in providing researchers with the entire simulation experience and examining the results to make 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 [90, 91].

5. Conclusion

This bibliometric study provides an overall picture of articles related to ABM that are present in the SSCI database. The SSCI database was searched for papers related to ABM published between 1995 and 2016. The number of papers related to ABM increased steadily between 1995 and 2013. The most productive countries were the United States, England, and Germany, whereas the most productive institutions were the University of Michigan, University of Groningen, and University of Illinois. The literature was scattered across a wide range of subject areas, and the main subject areas were primarily the social sciences (interdisciplinary), economics, computer science (interdisciplinary), and environmental studies. Lambin et al. [63] was the most influential paper with regard to citation count.

The GHSOM has all of the benefits of the SOM, providing a map from a higher-dimensional input space to a lower-dimensional map space and globally orienting independently growing maps in individual layers of the hierarchy, thus facilitating navigation across the branches. The results of the GHSOM in this study indicate the main topics of ABM research for any specific country. Some interpretation reveals topic analysis and indicates relationships among different disciplines.

In this study, the GHSOM results support those of Meyer et al. [31] and Chiang et al. [51]. However, they performed cocitation analysis to visualize the intellectual structure of social simulation and its development. Clusters in their dataset included 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 *Journal of Artificial Societies and Social Simulation* articles, whereas this study provided a comprehensive analysis covering all literature related to ABM in the SSCI database.

This study had one limitation. Node 4-21-5, representing 482 articles, did not cluster into some of the specific key terms. Approximately 450 articles could not be clustered into specific key terms after attempting $\tau 1$ and $\tau 2$; this was because approximately one-third of the articles had different research directions, whereas two-thirds of the articles elucidated the trend of ABM applications in science and technology fields.

The GHSOM results provided insight into future applications of ABM. ABM provides scholars in the fields of ecology and environment, economics, sociology, engineering, and business and management with a convenient and powerful tool for answering "how" and "what if" questions; in other words, complicated phenomena can be approximated by observing the interactions between simulated agents [13, 92, 93]. Unlike statistics and econometrics, which focus on the causal relationships between variables, ABM is mainly concerned with the replication of computational models, which Wilensky and Rand [94] argue may be more beneficial to the scientific community than the replication of physical experiments. Additionally, the patterns discovered through such observations may be used either to test existing theories or to explore new ones [95]. Axelrod [95] also suggests that ABM can address certain fundamental questions in many fields, thereby promoting interdisciplinary cooperation. When existing mathematical methods are insufficient, ABM is a useful tool for revealing the underlying unity of various science and technological fields.

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References

[1] Keller. EF, "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 Stefano Franchi, and Guven Guzeldere, 203-228. Cambridge: MIT Press, 2005.

[2] Von Neumann. J, Burks. AW, "Essays on Cellular Automata", University of Illinois Press, 1966.

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

[4] Macal. CM, North. MJ, "Tutorial on agent-based modeling and simulation", Journal of Simulation 2010; 4: 151-162.

[5] Schelling. TC, "Dynamic models of segregation", Journal of Mathematical Sociology 1971; 1:143-186.

[6] Schelling. TC, "Micromotives and Macrobehavior," New York: WW Norton, 1978.

[7] Tesfatsion. L, "Agent-based computational economics: Growing economies from the bottom up", Artificial Life 2002; 8:55-82.

[8] Macy. MW, Willer. R, "From factors to actors: Computational sociology and agent-based modeling", Annual Review of Sociology 2002b; 28:143-167.

[9] Sornette. D, Physics and financial economics (1776–2014): puzzles, Ising and agent-based models. Reports on Progress in Physics 77 (2014) 062001 (28pp), 1-28.

[10] Marshall. BDL, Galea. S, "Formalizing the role of agent-based modeling in causal inference and epidemiology", American Journal of Epidemiology 2014; 181(2). doi: 10.1093/aje/kwu274. 92-99.

[11] An. L, "Modeling human decisions in coupled human and natural systems: Review of agent-based models", Ecological Modelling 2012; 229:25-36.

[12] Bousquet. F, Le Page. C, "Multi-agent simulations and ecosystem management: a review", Ecological Modelling 2004; 176:313-332.

[13] Epstein. JM, Axtell. R, "Growing Artificial Societies", MIT press, Cambridge, 1996.

[14] Miller. JH, Page. SE, "Complex Adaptive Systems: An Introduction to Computational Models of Social Life", Princeton University Press, Princeton, New Jersey, 2007.

[15] Epstein. JM, (Ed.), "Generative Social Science: Studies in Agent-Based Computational Modeling", Princeton University Press, Princeton, New Jersey, 2006.

[16] Morrison. AE, Addison. DJ, "Assessing the role of climate change and human predation on marine resources at the Fatu-ma-Futi site, Tituila Island, American Samoa: an agent based model", Hemisphere 2008; 43:22-34.

[17] Yu. C, MacEachren. AM, Peuquet. DJ, Yarnal. B, "Integrating scientific modelling and supporting dynamic hazard management with a GeoAgentbased representation of human–environment interactions: a drought example in Central Pennsylvania, USA", Environmental Modelling & Software 2009; 24:1501-1512.

[18] Brown. DG, Robinson. DT, An. L, Nassauer. JI, Zellner. M, Rand. W, Riolo. R, Page. SE, Low. B, "Exurbia from the bottom-up: Confronting empirical challenges to characterizing complex systems", GeoForum 2008; 39(2):805-818.

[19] Batty. M, "Cities and Complexity: Understanding Cities with Cellular Automata, Agent-Based Models, and Fractals", The MIT Press, Cambridge, Massachusetts, 2007.

[20] Benenson. I, Torrens. PM, "Geosimulation: Automata-Based Modelling of Urban Phenomena", Wiley, West Sussex, UK, 2004.

[21] Gimblett. HR, "Integrating geographic information systems and agent-based technologies for modelling and simulating social and ecological phenomena", In: Gimblett, H.R. (Ed.), Integrating Geographic Information Systems and Agent-Based Techniques for Simulating Social and Ecological Processes. Oxford University Press, New York, 1-20, 2002.

[22] Hare. M, Deadman. P, "Further towards a taxonomy of agent-based simulation models in environmental management", Mathematics and Computers in Simulation 2004; 64:25-40.

[23] Entwisle. B, "Putting people into place", Demography 2007; 44:687-703.

[24] Goodchild. MF, "The validity and usefulness of laws in geographic information science and geography", Annals of the Association of American Geographers 2004; 94:300-303.

[25] Ostrom. E, "A diagnostic approach for going beyond panaceas", Proceedings of the National Academy of Sciences 2007; 104:15181-15187.

[26] Ostrom. E, "A general framework for analyzing sustainability of social–ecological systems", Science 2009; 35:419-422.

[27] Bithell. M, Brasington. J, Richards. K, "Discrete-element, individual-based and agent-based models: tools for interdisciplinary enquiry in geography?", Geoforum 2008; 39:625-642.

[28] Matthews. RB, Gilbert. NG, Roach. A, Polhill. JG, Gotts. NM, "Agent-based land-use models: a review of applications", Landscape Ecology 2007;22:1447-1459.

[29] An. L, Linderman. M, Qi. J, Shortridge. A, Liu. J, "Exploring complexity in a human–environment system: an agent-based spatial model for multidisciplinary and multi-scale integration", Annals of Association of American Geographers 2005; 95:54-79.

[30] Rindfuss. R, Entwisle. B, Walsh. S, Mena. C, Erlien. C, Gray. C, "Frontier land use change: synthesis. challenges, and next steps", Annals of the Association of Geographers 2007; 97:739-754.

[31] Meyer. M, Lorscheid I, Troitzsch. KG, "The Development of Social Simulation as Reflected in the First Ten Years of JASSS: A Citation and Co-Citation Analysis", Journal of Artificial Societies and Social Simulation 2009; 12:A224-A243.

[32] Zenobla. B, Weber, C, Daim. T, "Artificial markets: A review and assessment of a new venue for innovation research", Technovation 2009; 29:338-350.

[33] Choi. DG, Lee. YB, Jung. MJ, Lee. H, "National Characteristics and Competitiveness in MOT Research: A Comparative Analysis of Ten Specialty Journals, 2000-2009", Technovation 2012; 32:9-18.

[34] Lee. S, Yoon. B, Park. Y, "An Approach to Discovering New Technology Opportunities: Keyword-Based Patent Map Approach", Technovation 2009; 29:481-497.

[35] Cornelius. B, Persson. O, "Who's Who in Venture Capital Research", Technovation 2006; 26:142-150.

[36] Giovanni. A, D'Angelo. CA, Di Costa. F, Solazzi. M, "University-Industry Collaboration in Italy: A Bibliometric Examination", Technovation 2009; 29:498-507.

[37] Langton. C, "Artificial life", In: Langton, C. (Ed.), Artificial Life. Addison-Wesley, Reading, 1-47, 1988.

[38] Chiang. JK, Kuo. CW, Yang. YH, "A Bibliometric Study of E-learning Literature on SSCI Database", Lecture Note of Computer Science (LNCS), Springer Verlag, 2010.

[39] Leydesdorff, L., "Towards a Theory of Citation. A Reaction to MacRoberts & MacRoberts", Scientometrics12 1987, 287-291.

[40] Price, Derek, J. deSolla, "Networks of Scientific Papers -The pattern of bibliographic references indicates the nature of the research front", Science Journal, Vol. 149, Issue 3683, 1965, 157-162.

[41] Chiang. JK, Yang. YX, "Multi-layer visual presentation of annual research topics using growing hierarchical self-organizing map", Journal of Library and Information Science Research 2012; 6:2 (June 2012):1-35.

[42] Chau. M, Huang. Z, Qin. J, Zhou. Y, Chen. H, "Building a scientific knowledge web portal: The NanoPort Experience", Decision Support Systems 2006; 42:1216-1238.

[43] Ding. Y, Chowdhury. G, Foo. S, "Bibliometric cartography of information retrieval research by using co-word analysis", Information Processing & Management 2001; 37:817-842.

[44] Grupp. H, Schmoch. U, "Perception of Scientification as Measured by Referencing Between Patents and Papers", In Dynamics of Science-Based Innovation, edited by Hariolf Grupp, 73-128. Springer Verlag, Heidelberg, 1992.

[45] 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 2003; 54:462-468.

[46] Noyons. E, "Bibliometric mapping of science in a policy context", Scientometrics 2001; 50:83-98.

[47] Noyons. E, van Raan. T, "Monitoring scientific developments from a dynamic perspective: Self-organized structuring to map neural network research", Journal of the American Society for Information Science 1998; 49:68-81.

[48] Chiang. JK, Tseng. ZX, Yu. AC, :Developing a Novel Hybrid Sentiment Analysis Method – on Case of Taipei 2017 9th Summer Universiade", ICATI (International Conference on Advanced Technology Innovation), 2018a.

[49] Chiang. JK, Kuo. NF, Lin. W, "Extracting Information from Social Media to Tract Financial Market Risks", 2018 29th ICIM Conference (forthcoming), 2018b.

[50] Bhavsar. K, Kumar. N, Dangeti. P, "Classification of Emails Using Deep Neural Networks After Generating TF-IDF", In Nature Language Processing with Python Cookbook. Packt pub. 238-241, 2017.

[51] Chiang. JK, Chen. CC, "Sentimental Analysis on Big Data–On Case of Financial Document Text Mining to Predict Sub-Index Trend", 5th International Conference on Computer Sciences and Automation Engineering (ICCSAE 2015), 423-428, 2015.

[52] Shih. J-Y, Chang. Y-J, Chen. W-H, "Using GHSOM to Construct Legal Maps for Taiwan's Securities and Futures Markets", Expert Systems with Applications 2008; 34:850-858.

[53] Wolfram. D, "Applied Informetrics for Information Retrieval Research", Greenwood Publishing Group, 2003.

[54] Rauber. A, Merkl. D, Dittenbach. M, "The growing hierarchical self-organizing map: Exploratory analysis of high-dimensional data", IEEE Transactions on Neural Networks 2002; 13:1331.

[55] Salton. G, "Automatic Text Processing: The Transformation, Analysis, and Retrieval of Information by Computer", Addison-Wesley, Reading, 1989.

[56] Chiang. JK, "Aspect-level Sentiment Analysis based on Social Network Analysis Technique - on Cases of Opinion Mining of Instant Messenger Apps", 2014 25th ICIM Confernece, TaiChung Taiwan, May, 2014.

[57] Kohonen. T, Kaski. S, Lagus. K, Salojarvi. J, Honkela. J, Paatero. V, Saarela. A, "Self organization of a massive document collection", IEEE Transactions on Neural Networks 2000; 11:574-585.

[58] Kohonen. T, "Self-organized formation of topologically correct feature maps", Biological Cybernetics 1982; 43:59-69.

[59] Dittenbach. M, Rauber. A, Merkl. D, "Uncovering hierarchical structure in data using the growing hierarchical self-organizing map", Neurocomputing 2002; 48:199-216.

[60] Li. S-T, Chang. W-C, "Design and evaluation of a layered thematic knowledge map system", Journal of Computer Information Systems 2009; 49.

[61] Campanario. J, "Using neural networks to study networks of scientific journals", Scientometrics 1995; 33:23-40.

[62] Tsaih. R-H, Lin. W-Y, Huang. S-Y, "Exploring fraudulent financial reporting with GHSOM", Intelligence and Security Informatics 2009; 31-41.

[63] Lambin. EF, Geist. HJ, Lepers. E, "Dynamics of land-use and land-cover change in tropical regions", Annual Review of Environment and Resources 2003; 28:205-241.

[64] Parker. DC, Manson. SM, Janssen. MA, Hoffmann. MJ, Deadman. P, "Multi-agent systems for the simulation of land-use and land-cover change: A review", Annals of the Association of American Geographers 2003; 93:314-337.

[65] Anderson. P, "Complexity theory and organization science", Organization Science 1999; 10:216-232.

[66] Macy. MW, Willer. R, "From factors to actors: Computational sociology and agent-based modeling", Annual Review of Sociology 2002a; 28:143-166.

[67] Faratin. P, Sierra. C, Jennings. NR, "Using similarity criteria to make issue trade-offs in automated negotiations", Artificial Intelligence 2002; 142:205-237.

[68] Bowles. S, Gintis. H, "The evolution of strong reciprocity: Cooperation in heterogeneous populations", Theoretical Population Biology 2004; 65:17-28.

[69] Rivkin. JW, Siggelkow. N, "Balancing search and stability: Interdependencies among elements of organizational design", Management Science 2003; 49:290-311.

[70] Bunn. DW, "Forecasting loads and prices in competitive power markets", Proceedings of the IEEE 2000; 88:163-169.

[71] Panait. L, Luke. S, "Cooperative multi-agent learning: The state of the art", Autonomous Agents and Multi-Agent Systems 2005; 11:387-434.

[72] Bower. J, Bunn. DW, "Model-based comparisons of pool and bilateral markets for electricity", Energy Journal 2000; 21:1-29.

[73] Fandango. A, "Chapter 13 :Deep Reinforcement Learning", In Mastering TensorFlow. Packt pub, 332-355, 2018.

[74] Manson. SM, "Simplifying complexity: A review of complexity theory", Geoforum 2001; 32:405-414.

[75] Chen. S-H, Yeh. C-H, "Evolving traders and the business school with genetic programming: A new architecture of the agent-based artificial stock market", Journal of Economic Dynamics & Control 2001; 25:363-393.

[76] Raberto. M, Cincotti. S, Focardi. SM, Marchesi. M, "Agent-based simulation of a financial market", Physica A 2001; 299:319-327.

[77] Windrum. P, Birchenhall. C, "Structural change in the presence of network externalities: A co-evolutionary model of technological successions", Journal of Evolutionary Economics 2005; 15:123-148.

[78] Delre. SA, Jager. W, Bijmolt. THA, Janssen. MA, "Targeting and timing promotional activities: An agent-based model for the takeoff of new products", Journal of Business Research 2007; 60:826-835.

[79] Barbesino. P, "Towards a post-foundational understanding of community", Kybernetes 1997; 26:689-702.

[80] Bhattacharyya. S, Ohlsson. S, "Social creativity as a function of agent cognition and network properties: A computer model", Social Networks 2010; 32:263-278.

[81] Dawkins. R, "The Selfish Gene", Oxford University Press, New York, 2006.

[82] Hamilton. WD, "The genetical theory of social behaviour, I, II", Journal of Theoretical Biology 1964; 7:17-52.

[83] Trivers. RL, "Evolution of reciprocal altruism", Quarterly Review of Biology 1971; 46:35-57.

Journal of Engineering Technology

Volume 6, Special Issue (Emerging Trends in Engineering Technology) March. 2018, PP. 50-70

RESEARCH ARTICLE -ENGINEERNG TECHNOLOGY

[84] Wilson. EO, "Sociobiology: The new synthesis", Traduccion castellana, 1975.

[85] Hoffmann. R, "Twenty years on: The evolution of cooperation revisited", Journal of Artificial Societies and Social Simulation 2000; 3:1390-1396.

[86] Bandini. S, Manzoni. S, Vizzari. G, "Agent based modeling and simulation: An informatics perspective", Journal of Artificial Societies and Social Simulation 2009; 12:A51-A66.

[87] Nikolai. C, Madey. G, "Tools of the trade: A survey of various agent based modeling platforms", Journal of Artificial Societies and Social Simulation 2009; 12.

[88] Heath, B., Hill, R., Ciarallo, F., "A survey of agent-based modeling practices (January 1998 to July 2008)", Journal of Artificial Societies and Social Simulation 12 (4) 2009, http://jasss.soc.surrey.ac.uk/12/4/9/9.pdf.

[89] David. N, Sichman. JS, 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 2005; 8.

[90] Becker. J, Niehaves. B, Klose. K, "A framework for epistemological perspectives on simulation", Journal of Artificial Societies and Social Simulation 2005; 8.

[91] Schmid. A, "What is the truth of simulation?" Journal of Artificial Societies and Social Simulation 2005; 8.

[92] Bui. T, Lee. J, "An agent-based framework for building decision support systems", Decision Support Systems 1999; 25:225-237.

[93] Epstein. JM, "Agent-based computational models and generative social science", Complexity 1999; 4:41-60.

[94] Wilensky. U, Rand. W, "Making models match: Replicating an agent-based model", Journal of Artificial Societies and Social Simulation 2007; 10:2.

[95] Axelrod. R, "Agent-Based Modeling as a Bridge **B**etween Disciplines", In Handbook of Computational Economics, edited by Leigh Tesfatsion, and Kenneth L. Judd, 1565-1584. Elsevier, 2006.

[96] Tesfatsion. L, "Introduction to the special issue on agent-based computational economics", Journal of Economic Dynamics and Control 2001; 25:281-293.