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Mapping the knowledge frontiers and evolution of decision making based on agent-based modeling

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ABSTRACT

With increasing attention paid to the application of agent-based modeling in decision-making issues, a large number of related studies have been published in management science and operational research areas. This study adopts multiple methods, including bibliometric mapping, text mining, and qualitative analysis, to comprehensively review relevant research to explore knowledge frontiers and evolution in decision-making research based on agent-based modeling (DM-ABM). This review is based on 1190 relevant journal articles from the Web of Science Core Collection dataset and 37,167 collectively cited references of the articles. The top ten most-cited studies that constitute the intellectual milestones of DM-ABM were identified. Keywords and research topics develop rapidly; recent research have paid most attention to the keywords "model," "system," and "simulation" and topics "learning," "contracts," "protocols," and "self-learning." The top 24 references with the strongest citation bursts were displayed to show that the area was increasingly active from 2001 to 2010. Transition points were mapped to reveal the top five studies with the highest betweenness centrality, which considerably influences knowledge evolution. Then, the top three clusters are identified as the frontier areas and analyzed by text mining, including intelligent agents, model validation, and collaborative decision making. Finally, the most recent research in this field is investigated, and four future research directions are proposed: the advanced intelligence of agents, approach to reality, group decision making, innovative modeling methodologies and diversified applications.

1. Introduction

Decision making is integral in management and operational research. Research on decision making is of great importance because the insights that it provides can improve the effectiveness of decision making, which ultimately contributes to its management in both academic and practical areas. Decision making is a complex task that involves various perspectives, constraints, and variables [1,2]. Previous studies have investigated decision making from different perspectives, including theories, methods, stakeholders in decision making, multi-criteria decision making, and decision making in different application fields [3–5]. In recent years, research interest in simulation methods to model complex decision-making systems has increased. Among the simulation approaches, including discrete event simulation, system dynamics, and agent-based modeling (ABM), ABM is the most widely used method in management and operational research [6].

According to Gilbert [7], ABM "is a computational method that enables a researcher to create, analyze, and experiment with models composed of agents that interact within an environment". ABM has three attributes: autonomy (agents act by themselves rather than being controlled by humans, other agents, or entities); cooperation (agents can achieve what they cannot achieve on their own with cooperation); and learning (agents evolve over time, adapt to the environment, and enhance performance) [8,9]. Owing to these three attributes, agent-based models are suitable for simulating the behaviors and interactions of heterogeneous agents [10]. By modeling numerous agents' behaviors (micro-level), ABM can help understand the overall system performance (macro-level). Therefore, ABM is considered a "bottom-up" modeling method in social sciences, as shown by Epstein and Axtell [11]. The main advantages of agent-based models include parallel processing, inherently distributed intelligent agents, and dynamic environments, which make such models useful tools for simulating complex decision-making problems.

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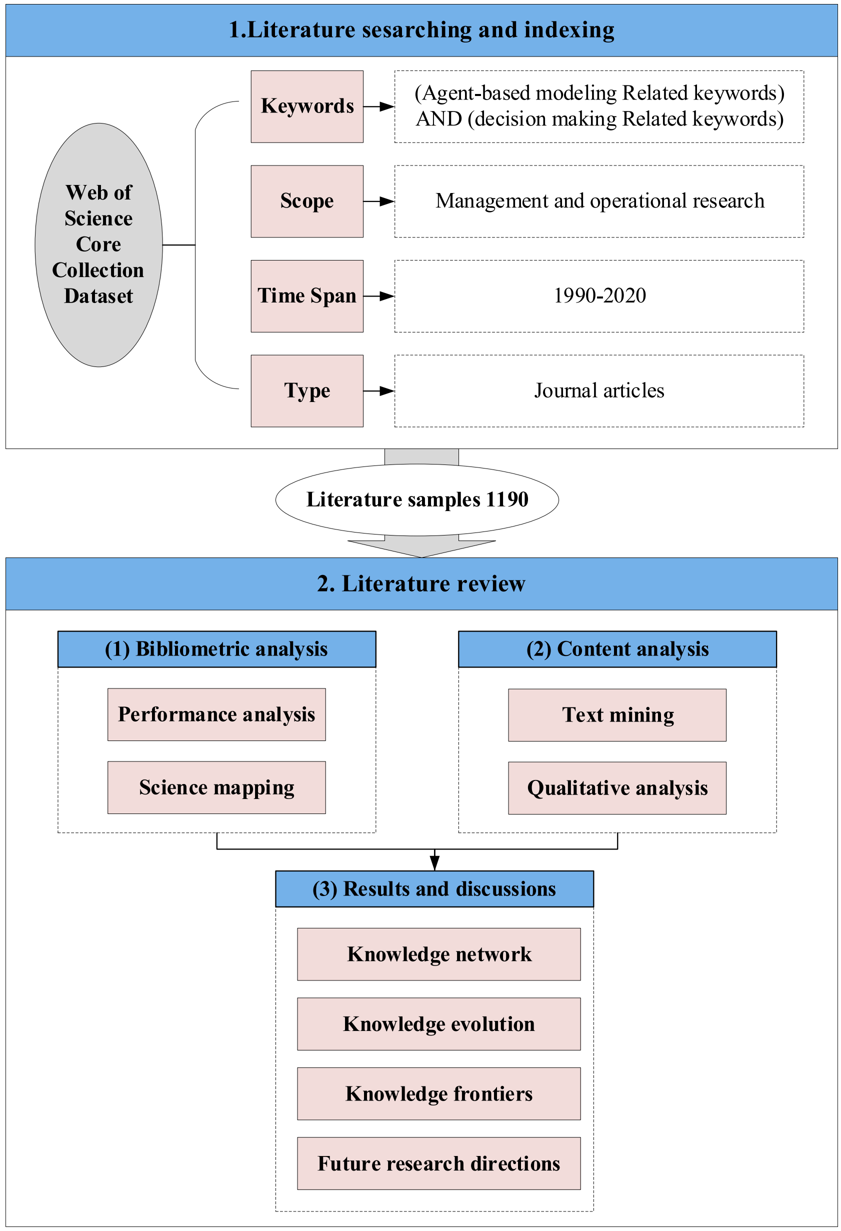

Fig. 1. Diagram of the research framework.

ABM has recently been widely applied in research on decision making (DM-ABM), including in different areas (e.g., environmental management, supply chain management, project management, and public policy), from different perspectives (e.g., optimization, process, and stakeholder collaboration in decision making), and using different methods (e.g., multi-criteria decision making, hybrid modeling, and scenario analysis) [12–14]. Previous review papers have made remarkable strides in this area; however, most focus on tackling a specific issue of DM-ABM [15–18]. Few studies have provided a full view of this area, focusing on comprehensively and systematically understanding the evolutionary process, frontiers, milestones, and key issues of DM-ABM.

To bridge this gap, this study provides an overview of the status of ABM research to support further academic work in the area of decision making and, in particular, to illustrate the evolution process, frontiers, milestones, and key issues of DM-ABM. This study addressed the following research questions:

(1) What are the most important studies in the research area of DM-ABM?

(2) How have studies evolved in recent decades, including changes in keywords, topic development, and phases of research?

(3) What are the relationships and interactions among studies in the co-citation network?

(4) What are the frontiers of knowledge in this area? And what are the research directions of future studies?

2. Methodology

2.1. Research framework

Fig. 1 shows the research framework used in this study. Literature related to DM-ABM was collected from the Web of Science Core Collection dataset. The literature review was conducted in three steps: (1) bibliometric analysis, exploring intellectual milestones, knowledge evolution, and knowledge frontiers; (2)

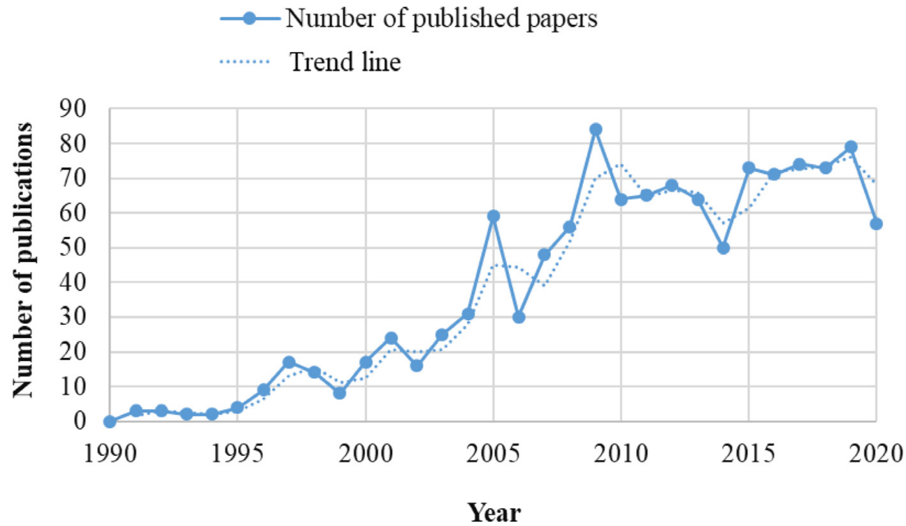

Fig. 2. Trend of research interests in DM-ABM.

content analysis, combining research clustering and text mining of the frontier areas; and (3) discussions, identifying future research directions based on bibliometric analysis and content analysis.

2.2. Data collection

This study collected detailed information from DM-ABM-related studies in the Web of Science Core Collection dataset. The collected information included titles, authors, subjects, publication years, keywords, abstracts, and cited references. This study used multiple terms referring to "decision making" and "agent-based modeling" to carry out the literature search in the dataset. A Boolean operator was also used in the topic search. The search strategy was as follows.

Database: Web of Science Core Collection dataset over the period 1990–2020.

Topic search: Multiple ABM-related terms were combined with decision-making associated terms in the following strings in the Boolean operator: (multi-agent OR multiagent OR agent based OR agent-based) AND (decision making OR mak* decision* OR mak* a decision OR made decision* OR made a decision).

Final dataset: A dataset comprising 1190 papers and 37,167 collectively cited references of the papers was obtained. The types of papers included journal articles, review articles, and proceedings. The search was conducted on December 4, 2020. A subsequent search could have provided more results. Fig. 2 shows that the number of published papers on DM-ABM has risen over time, indicating an increasing research interest in this area.

2.3. Bibliometric mapping

Bibliometric mapping applies mathematical and statistical methods to analyze the knowledge domain of a research area [19]. Two main methods are often used to explore an area, which are performance analysis and science mapping [20–22]. Performance analysis uses important bibliometric indicators to measure the scientific impact and citations obtained, which provides valuable implications for evaluating the quality of studies. Science mapping reveals the conceptual or intellectual structure of knowledge and its evolution.

2.3.1. Performance analysis

This study analyzes the impact of critical studies on knowledge development in the DM-ABM area from three aspects: document co-citation analysis (DCA), citation burst, and transition points, in which typical indicators can be calculated to indicate the influence of studies.

(1) DCA

Co-citation analysis, one of the most extensively used methods in bibliometric mapping, includes DCA, journal co-citation analysis, and author co-citation analysis [23]. DCA is the most commonly used method for analyzing relationships among studies. Co-citation describes two studies that are co-cited in a subsequent work [24], which indicates a close relationship between them. If the two studies are frequently cited by other researchers, they are highly likely to share similar topics and concepts [25]. DCA is normally shown as a co-citation network in which the nodes refer to studies and the links are the co-citation frequencies between the nodes:

$$L(X_i - X_j) = \sum w_{ij} \tag{1}$$

where $L(X_i - X_j)$ is the link between nodes X_i and X_j, and w_{ij} is the number of times the nodes X_i and X_j are co-cited by subsequent documents. CiteSpace software was used to automatically calculate the co-citation frequency of the studies. In this way, DCA can identify the most highly cited work that is considered to lay the knowledge base and intellectual milestones of previous research [26]. Therefore, this study conducted DCA to analyze the most frequently cited studies to understand the intellectual knowledge milestones of the DM-ABM area.

(2) Citation bursts

A citation burst is a typical indicator of the most valuable publications in a research area [27]. A citation burst indicates that a particular research is followed by a surge in citations because it has attracted an extraordinary degree of attention from the research community. If a cluster of studies contains numerous citation bursts, particularly in recent years, it is considered an active area of research and an emerging trend. Therefore, citation bursts can also be used to identify the development tendencies of a research area.

Citation burst detection is of value in identifying studies that increase sharply when compared to their peers [28]. CiteSpace software can conduct burst detection based on Kleinberg's algorithm [29]. The strength of the burst refers to the level of impact

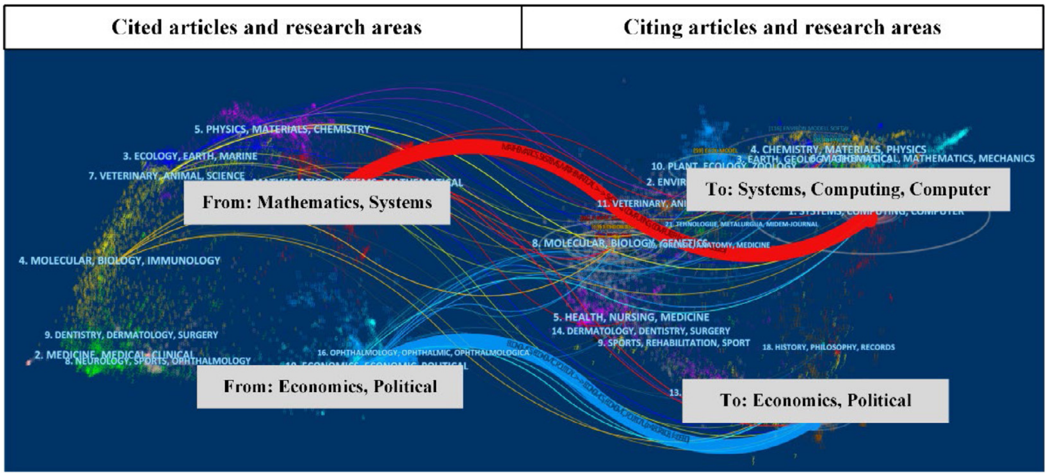

Fig. 3. The relation between citing and cited articles.

the study exerts on knowledge development, and the length of the burst reveals the duration of the impact.

(3) Transition points

Knowledge transition points are interdisciplinary studies that extend into new research areas. They are usually deployed in DCA to identify key points that may have changed the knowledge evolution and shifted research development [30]. They act as brokers in the knowledge network and as bridge subnetworks. In graph theory, the transition points can be identified using the betweenness centrality indicator. Studies with high betweenness centrality are transition points in the knowledge network. Betweenness centrality measures the extent to which nodes control exchanges between subgroups in the network. The betweenness centrality was calculated using Eq. (2):

$$C_B(X_i) = \sum_{j}^{n} \sum_{k}^{n} \frac{g_{jk}(X_i)}{g_{jk}} \; j < k, \text{ and } i \neq j \neq k \tag{2}$$

where $C_B(X_i)$ is the betweenness centrality, and $g_{jk}(X_i)$ is the number of shortest paths between nodes X_j and X_k passing through node X_i, indicating that betweenness centrality is calculated as the number of shortest paths passing through node X_i divided by the number of all paths passing through X_i. This study adopts CiteSpace to calculate the betweenness centrality of the research and identifies the transition points in the DM-ABM area for further analysis.

2.3.2. Science mapping

This study shows knowledge evolution by mapping keyword development and the evolution of research topics over time. The intellectual structure of the knowledge domain was mapped using a cluster analysis.

(1) Keyword analysis

This study explored the knowledge evolution of the DM-ABM domain based on keyword analysis, which has been extensively used to investigate the knowledge development process in previous research. The CiteSpace software was adopted for keyword analysis.

First, the most popular keywords in the dataset were identified based on the frequency with which they were mentioned in relevant research. The development trends of the keywords were analyzed by summarizing the keyword counts in different periods.

Then, the evolution of topics in the DM-ABM area is explored based on keyword concurrence analysis. This study divided keywords into several groups; keywords with high concurrence were considered in the same group. The scale of the groups was also mapped to show the development of topics over time.

(2) Cluster analysis

Based on DCA, cluster analysis was conducted to identify co-citation clusters, thereby revealing the underlying intellectual structures. According to Schneider [31], cited papers serve as symbols of scientific ideas, methods, and experiments. These are further extended to clusters extracted from the citation contexts of the cited documents. Therefore, interpreting the clusters of cited documents and the interrelationships between clusters is the focus of the DCA. Cluster analysis depends on the similarity of nodes in the co-citation network. Alternative similarity measures exist, including cosine, Dice, and Jaccard similarity coefficients. CiteSpace can help identify clusters using a clustering algorithm, the log-likelihood ratio, which is a commonly used method for cluster analysis.

2.4. Text mining

Text mining is the process of transforming unstructured text into a structured format to identify meaningful patterns, new insights, and knowledge in text documents [32]. This method has been widely adopted to extract information from various resources. Existing review papers, such as Romero-Silva and de Leeuw [33], also use text mining to analyze knowledge development paths in operational research. This study adopts text mining to explore research trends in the frontier areas of the DM-ABM. The computer-assisted tool, Leximancer, was adopted to mine the frontier area to identify critical themes and concepts. Knowledge maps were generated to show the critical themes and concepts in each frontier area.

3. Results and discussion

This study shows the research findings from three perspectives: knowledge networks, evolution, and frontiers.

3.1. Knowledge network

3.1.1. Relation between citing and cited articles

This study identified the relationship between citing and cited articles in the dataset using CiteSpace, as shown in Fig. 3. The research areas are defined by Web of Science categories, which are illustrated by different colors and numbers. The research areas of the cited and citing articles are shown on the left and right sides, respectively. The citation relations between the research areas

Table 1
Top 10 most cited documents in the DM-ABM field.

Document title	Year	Cite references	Citation counts in CiteSpace	Citation counts in Google Scholar
Multi-agent systems for the simulation of land-use and land-cover change: A review	2003	Parker et al. [34]	12	2331
Tutorial on agent-based modelling and simulation	2010	Macal and North [35]	11	2936
Agent-based modeling: Methods and techniques for simulating human systems	2002	Bonabeau [36]	9	5205
On agent-based software engineering	2000	Jennings [37]	9	3014
An introduction to multi-agent systems	2002	Wooldridge [38]	9	12 634
Complex adaptive systems: An introduction to computational models of social life	2007	Miller and Page [39]	8	3164
Developing theory through simulation methods	2007	Davis et al. [40]	8	1350
Managing Business Complexity Discovering Strategic Solutions With Agent-Based Modeling and Simulation	2007	North and Macal [41]	8	1167
Agent-based land-use models: A review of applications	2007	Matthews et al. [42]	7	951
Negotiation-based collaborative planning between supply chains partners	2005	Dudek and Stadtler [43]	7	391

are illustrated by these links. The width of the links indicates the strength of the relationships. The wider the links, the greater the strength of the relationship.

According to the results in Fig. 3, there are two main links between citing and cited articles. One link indicates that articles in the "system and computing" area mainly cite articles from "mathematics and systems", while the other link indicates that articles in the "economics and politics" area mainly cite articles from "economics and politics". The cross-links between the two main links were limited, with only a few minor links. Therefore, studies on DM-ABM in the "system and computing" area mainly learn from the "mathematics and systems" area, whereas citing and cited "economics and politics" papers are in a relatively closed system. Further, studies in the two main areas (i.e., system and computing, economics, and politics) have limited interactions, which means that although ABM studies in these two domains are active, they are almost isolated between these two domains. This is probably because the applications of ABM differ between the two domains; one is mainly for automatic systems and the other is mainly for human behaviors.

3.1.2. Intellectual milestones

DCA is an important part of data analysis in bibliometric mapping research and can help scholars identify critical points in the knowledge development path.

Table 1 shows the top ten most-cited documents based on their co-citation frequency, and their citation counts in CiteSpace and Google Scholar are also provided. The most cited studies include six journal articles, three books, and one proceedings paper, constituting the intellectual milestone of DM-ABM and contributing considerably to theory development and model application. It could be seen that the citation frequency of the documents in CiteSpace differs from that in Google Scholar. This is because DM-ABM-associated research may be cited by studies beyond the decision-making area or may not be relevant to DM-ABM in the databases. In this study, the cited documents were restricted to references of research focusing on DM-ABM in the Web of Science Core Collection dataset, which allowed us to identify meaningful citations that have contributed to the knowledge development of DM-ABM.

The most frequently cited document was the journal article by Parker et al. [34], with 12 citations in the DM-ABM dataset. Parker et al. [34] reviewed the development and application of multi-agent systems of land use/cover change (MAS/LUCC models), combining cellular models with agent-based models to simulate critical actors' decision-making behaviors in landscapes. The strengths and challenges of MAS/LUCC models are also provided to indicate that the models are suitable for describing complex human–environment interactions, where decentralized and autonomous decision making is considered a key element. Parker et al. [34] inspired another highly cited review article by Matthews et al. [42], which further reviewed the application of agent-based models to multiple aspects of land use, including policy planning, participatory analysis, spatial patterns, social science concepts, and functions. Wooldridge [38] received the most citations from Google Scholar (12 634 times), far exceeding its peers in the dataset, indicating that it exerted more impact in the ABM field than in the DM-ABM field.

Most highly cited documents mention that ABM is suitable for modeling human-related decision-making behaviors in complex systems and complex adaptive systems. On this basis, multiple frequently cited documents provide foundational knowledge on modeling and simulating agents' interactions and decision making, together with the consideration of system complexity, such as Miller and Page [39] and North and Macal [41]. Macal and North [35] briefly introduced the concepts and foundations of ABM, analyzed the applications of ABM in various disciplines, such as biological science, computational social science, economics, and markets, and identified several toolkits to support the modeling process. Similarly, Bonabeau [36] analyzed the basic principles of ABM and discussed its application in addressing real-world business problems in the areas of flow, organization, market, and diffusion simulation. Dudek and Stadtler [43] applied ABM to supply chain coordination, in which control agents could be used to support the decision-making behaviors of functional agents.

3.2. Knowledge evolution

3.2.1. Development of keywords

As shown in Fig. 4, there are four waves of study in the DM-ABM area. The first wave occurred between 1991 and 2000. DM-ABM studies began in the 1990s and peaked in 1995 but dropped around 2000. The second wave was from 2001 to 2005; studies developed rapidly during this period, but dropped around 2005. The third wave (from 2006 to 2014) was a long and fast-developing period, but the number of studies declined slightly after 2012. The last wave was from 2015 to 2020, when the number of studies remained stable at a high level.

The development of keywords in the DM-ABM area in these four waves was analyzed using CiteSpace. The color of the bubbles represents the keywords and the size of the bubbles represents the frequency of the keywords. The larger the bubble, the higher

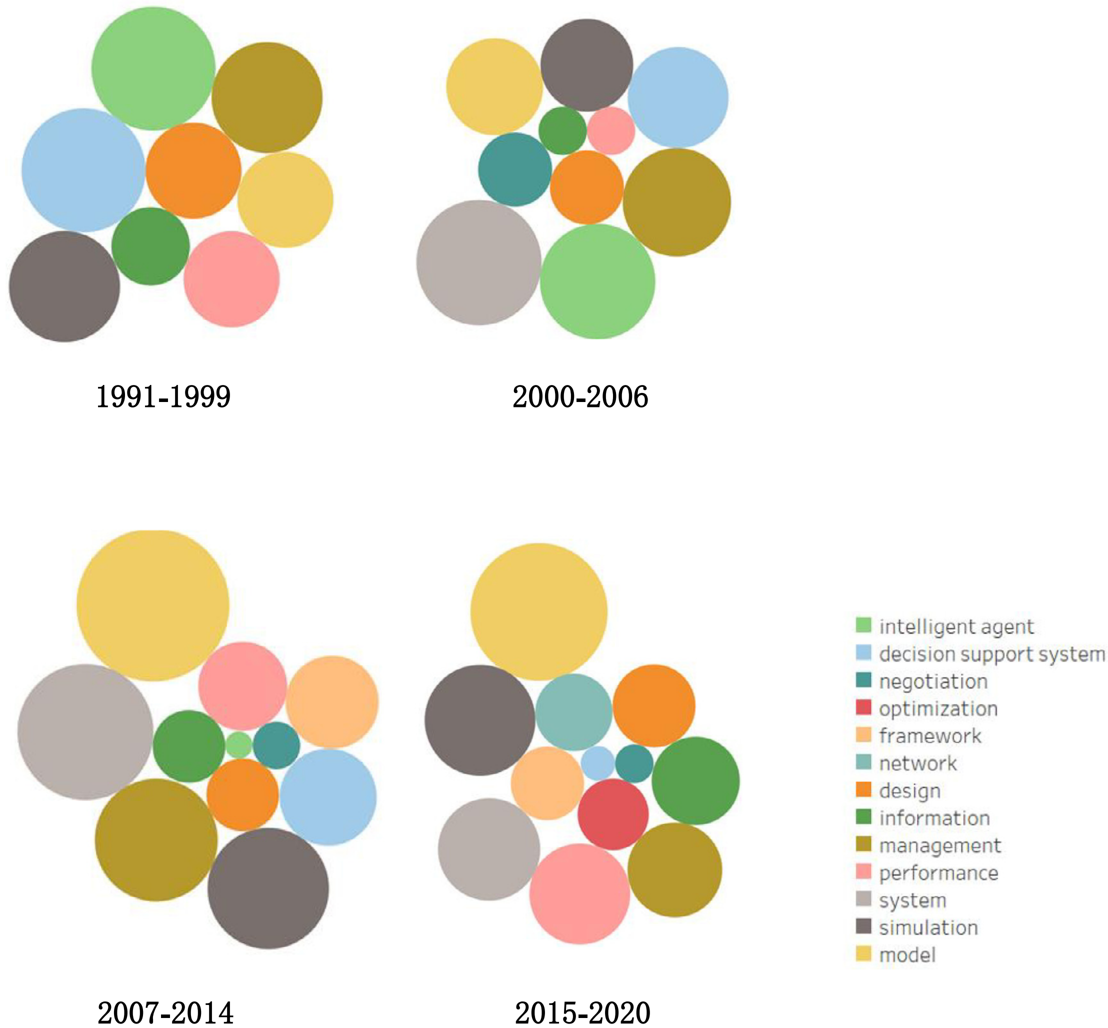

Fig. 4. The development of keywords in DM-ABM area.

is the frequency of the keyword (shown in Fig. 4). The development of keywords over the past 30 years can be identified based on different patterns.

From 1991 to 2000, the highest frequency keywords were "intelligent agent", "decision support system", "simulation", and "management". From 2001 to 2005, "system" becomes a new high-frequency keyword, with "model" developing quickly as well. From 2001 to 2005, "model" continues to develop and becomes the No. 1 keyword in this period. Some new keywords (e.g., "performance" and "framework") grow, while some fade away (e.g., "intelligent agent" and "negotiation"). The keyword patterns changed significantly from 2015 to 2020. The highest-frequency keywords are the "model", "simulation", "system", "performance", and "management". management. High-frequency keywords expanded during this period, and new keywords were generated (e.g., "optimization", "information", and "network").

In summary, high-frequency keywords have been developed dynamically over the last 30 years. There are four key features of the keyword development. First, high-frequency keywords have become more diverse over the last 30 years, which means that scholars in this area are interested in more diverse topics. Second, more studies have focused on "model", "system", and "simulation", which means modeling and simulating is a major stream in this area, especially in recent years. Third, some keywords continued to have high frequency (i.e., "management" and "simulation"). Fourth, traditionally hot keywords (e.g., "decision support system", "intelligent agent", and "negotiation") have faded in recent years.

3.2.2. The evolution of topics

Fig. 5 shows the results of topic evolution, where the colors of the nodes represent clusters, and the links represent the relations between the nodes. Table 2 lists the characteristics of the six groups of keywords, sorted by group size. The first group was Group 6, generated in the 1990s. The research in the 2000s was highly productive, with Groups 1, 2, and 4 becoming mainstream sequentially. Group 3 was active during 2010. Finally, the most notable topic was Group 5.

From the perspective of group size, Group 1 is the largest group, which focuses on "systems", "negotiation", and "optimization". Groups 2–5 were of similar size and focused on diverse topics. From the time perspective, Group 6 is the first group (also the smallest group) in the DM-ABM area, which focuses on the "supply chain", "coordination", and "operations". operations. The mean years in Groups 1, 2, and 5 were similar (2004 and 2005). Studies in the 2000s were active and diverse, focusing on "systems", "simulations", and "intelligent agents". Group 3 became active in the 2010s (mean year 2009), focusing on "modeling", "markets", and "learning". learning. "Learning" first appeared among the typical keywords in Group 3. Finally, Group 5 became

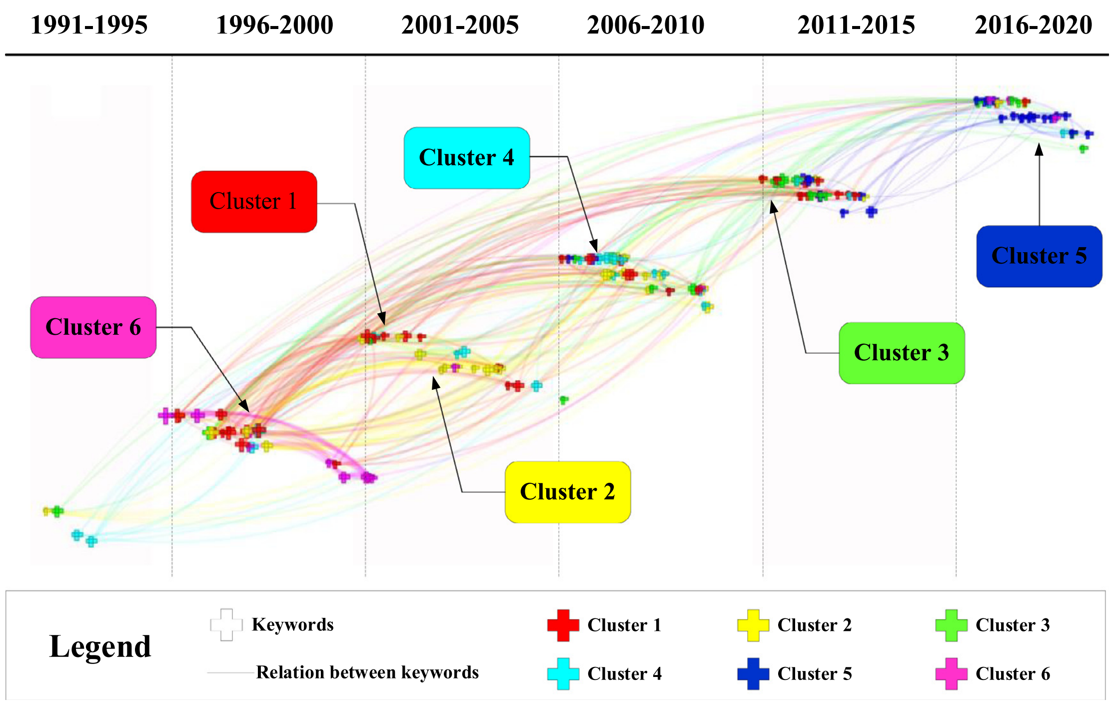

Fig. 5. The evolution of topics in DM-ABM area.

Table 2
The groups of keywords in DM-ABM area.

Group	Size	Mean year	Typical keywords
Group 1	42	2004	Systems, negotiation, optimization
Group 2	33	2004	Simulation, innovation, networks
Group 3	30	2009	Modeling, markets, learning, supply chain
Group 4	27	2005	System, intelligent agent, decision support
Group 5	25	2014	Learning, contract, protocol, self-learning
Group 6	16	2003	Supply chain, coordination, operation

active in recent years (mean year 2014), focusing on "learning", "contracts", "protocols", and "self-learning". This indicates that "learning" has become the No. 1 keyword in the latest group and that a related keyword, "self-learning", has become a typical keyword. Therefore, the topic on "learning" has shown significant development in the last five years.

3.2.3. The citation bursts of critical research

A citation burst detects a burst event that can last for a period to identify the most active area of research [30]. Publications with a surge in citations are then identified. Fig. 6 illustrates the top 24 references with the strongest citation bursts, which shows critical research with a high impact on the evolution of the DM-ABM area over time. The earliest citation burst occurred from 1997 to 2003, led by Wooldridge and Jennings [44], who provided theoretical and practical knowledge on the design and construction of intelligent agents and laid the foundation for subsequent agent-based research. Wooldridge and Jennings's [44] great influence on the knowledge area of DM-ABM could be characterized by up to seven years of citation bursts, far exceeding their peers.

The period from 2001 to 2010 generated the most bursts over the past few decades, with a focus on developing and applying agent-based systems/software to address multiple issues. For example, Jennings [37] explored the development of robust and scalable agent-based software to solve complex real-world problems in dynamic and uncertain environments, which inspired many citing studies with the highest strength of citation bursts (7.6309) from 2004 to 2007. The work by Parker et al. [34], who reviewed the application of multi-agent systems in land use, is also influential for having the longest time of citation bursts, together with Wooldridge and Jennings [44] among the top studies. Shen and Norrie [45] explored the key issues in developing agent-based manufacturing systems and their application in multiple areas, such as enterprise integration and supply chain management, with the top third strength (6.0394) of citation bursts. Rivkin is the most productive scholar among the top 24 references, providing up to three citation bursts during this period, focusing on the complexity of organizational strategies [46,47] and organizational sticking points on the fitness landscape [48].

The period from 2011 to 2014 was characterized by further theoretical development of agent-based simulation modeling. For example, Davis et al. [40] developed a roadmap to describe the theoretical development of simulation methods with high internal validity, as well as longitudinal, nonlinear, and process benefits. Harrison et al. [49] further demonstrated the nature and problems associated with using a simulation methodology in management research. Methodological issues and manufacturing systems deployed based on agent-based computations have also been explored [50].

In recent years, the theoretical development of multi-agent systems has been forwarded by Macal and North [35], who have contributed to the DM-ABM field by providing further foundational knowledge on multi-agent systems, with a citation burst strength of up to 7.6122. In terms of application, Chatfield and Pritchard [51] built a hybrid agent-based model to simulate decisions on return policy and the bullwhip effect of a supply chain, whereas Monostori et al. [52] emphasized cyber–physical production systems and highlighted that agent-based holonic systems are promising tools to support the decision making of complex systems for managing changes and disturbances.

3.2.4. Transition points

In addition to the development of keywords and the evolution of topics that indicate research trends in the DM-ABM area, we examine which studies are critical transition points in the knowledge domain. As mentioned in the Methodology section, nodes

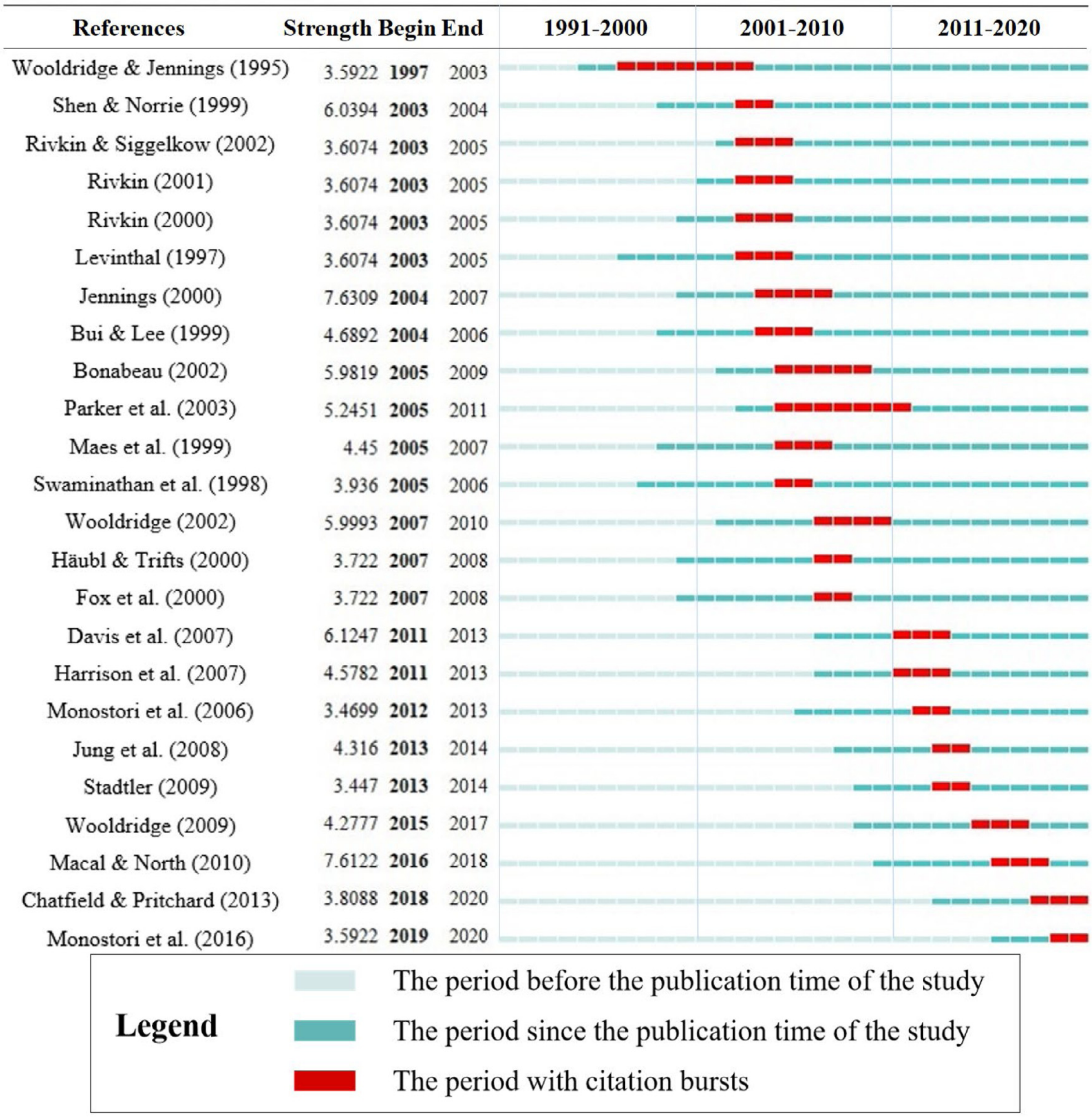

Fig. 6. Top 24 references with the strongest citation bursts over the years.

with higher betweenness centrality play a critical mediating role in knowledge evolution. These documents are noted as being interdisciplinary, connecting research areas, and acting as brokers in knowledge evolution.

Fig. 7 shows the top five transition points with the highest betweenness centralities in the co-citation network. As could be seen, the five nodes bridge at least two sub-networks of knowledge, thereby integrating research communities from different disciplines. The first transition point is the "introduction to multi-agent systems" by Wooldridge [38], who introduced such aspects of multi-agent systems as theory, design, and applications in different areas. Owing to its comprehensive content, numerous studies have been derived from this research, thereby providing an important foundation for future studies in different areas.

The studies with the second and third highest betweenness centrality are done by Kwon and Lee [53] and Lau et al. [54] respectively, which are both related to supply chain management, indicating the mediating role of supply chains issues in the area of DM-ABM. Kwon and Lee [53] bridge research on supply chain and collaboration mechanisms, which emphasizes the stakeholder/human perspective in supply chain management. Lau et al. [54] bridge research on supply chain and project scheduling, which emphasizes information/object in supply chain management. Lima et al. [55] ranks the fourth among the transition points, which is also associated with planning and scheduling, but extends to production planning. The fifth transition point conducted by Bonabeau plays a crucial role by integrating the insights of operation research with human systems in social science, indicating that agent-based modeling is an effective tool for simulating human systems, including human behaviors, organizations, and interactions [36]. Based on this point, a large research community on human systems has developed rapidly in recent years, as shown by the large and high-density sub-network in the upper left of Fig. 7.

3.3. Knowledge frontiers

3.3.1. Research clusters

Over the past two decades, DM-ABM has attracted wide attention and inspired the development of diverse topics. Fig. 8 illustrates the eight largest clusters identified by co-citation cohesiveness analysis, with the clusters ranked by size. The average

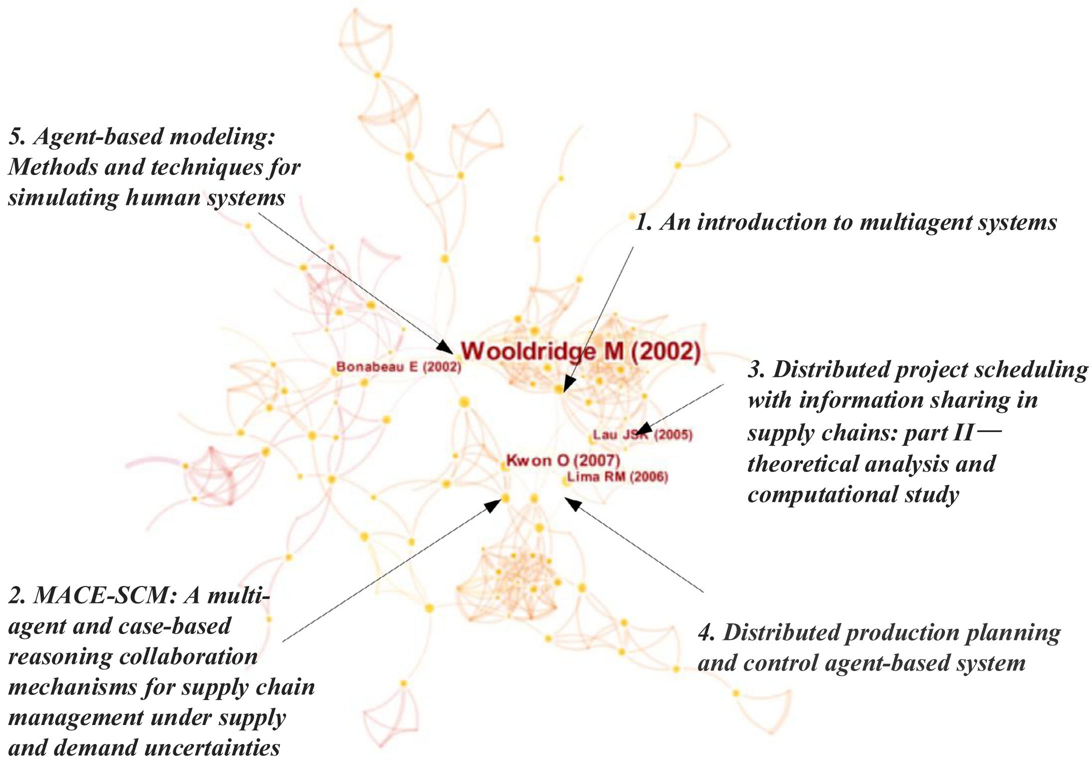

Fig. 7. The top five transition points in co-citation network.

publication year (APY) of the clusters indicates the development trends of topics in this area. The earliest cluster is #8 organizational search (size = 12, silhouette = 0.99, APY = 1999). This is in line with existing research, which finds that organizational decision making is an important topic that has triggered the development of DM-ABM studies. Subsequently, diverse themes emerged, such as #3 distributed decision making (size = 26, silhouette = 0.911, APY = 2002), #5 complexity (size = 16, silhouette = 0.927, APY = 2004), and #12 urban land use (size = 10, silhouette = 0.991, APY = 2004).

From the mutual interactions and long-term development of the themes, three frontier areas were derived: #0 intelligent agents (size = 40, silhouette = 0.862, APY = 2004), #1 model validation (size = 34, silhouette = 0.857, APY = 2007), and #4 collaborative decision making (size = 20, silhouette = 0.971, APY = 2008). The first two areas are the largest clusters, whereas the third has received relatively high attention in recent years. The results of text mining of the full texts of the three clusters are shown in the following section to explain the frontier topics in depth.

Fig. 9 shows the timeline of co-citation connections within and across the clusters. Cluster #0 intelligent agents emerged as early as 1997 and have been active in recent years, with several large nodes revealing highly co-cited documents. The dense links imply frequent co-citations within and across Cluster 0, indicating both internal and interdisciplinary concerns. Cluster #1 model validation started in 2000 and was more active from 2004 to 2008 than it was thereafter. Compared to other clusters, the third frontier area, Cluster #4, is a relatively new field that emerged in 2006 and has since become a popular research topic.

3.3.2. Frontier areas

This study adopts the text-mining software Leximancer to analyze the full texts of studies within three frontiers (Cluster #0, Cluster #1, and Cluster #4) to generate knowledge maps and explain the intellectual base.

Cluster #0 intelligent agents

Fig. 10 illustrates the knowledge map of cluster #0 produced by Leximancer. The themes within the cluster are indicated by the colored circles on the map. The themes were heat-mapped to reveal their significance, indicating that the most important theme was the hottest color (red). The nodes within the circles represent the concepts of the themes and the connections represent the semantic proximity between the nodes and themes. Hits denote the frequency of text blocks associated with the theme in the documents.

Fig. 10 shows that Cluster #0 is a large group that contains up to 12 themes. ABM and dynamic simulation modeling are the top two most influential themes in this cluster, indicating that many decision-making issues are dynamically considered and simulated using ABM. The hits column also shows that decision-making complexity and agent interactions are another two most frequently discussed themes in Cluster #0, revealing the complexity of decision-making processes. This is in line with previous research that finds that intelligent agents do not exist individually, but need to interact to analyze the decision-making environment and processes. Additionally, Fig. 10 demonstrates that information management, social issues, land-use change, and environmental impacts are important themes in the cluster, implying that decision-making issues with the use of intelligent agents in these topics have received intense attention over time.

Cluster #1 model validation

Cluster #1 was the second-largest cluster, with up to 10 themes. Fig. 11 shows that the hottest themes in this cluster include model development and decision-making processes, indicating that the process of developing a model to analyze decision-making behaviors has attracted significant research attention. The consumer diffusion network is another important theme with high hits in the text, showing that network modeling

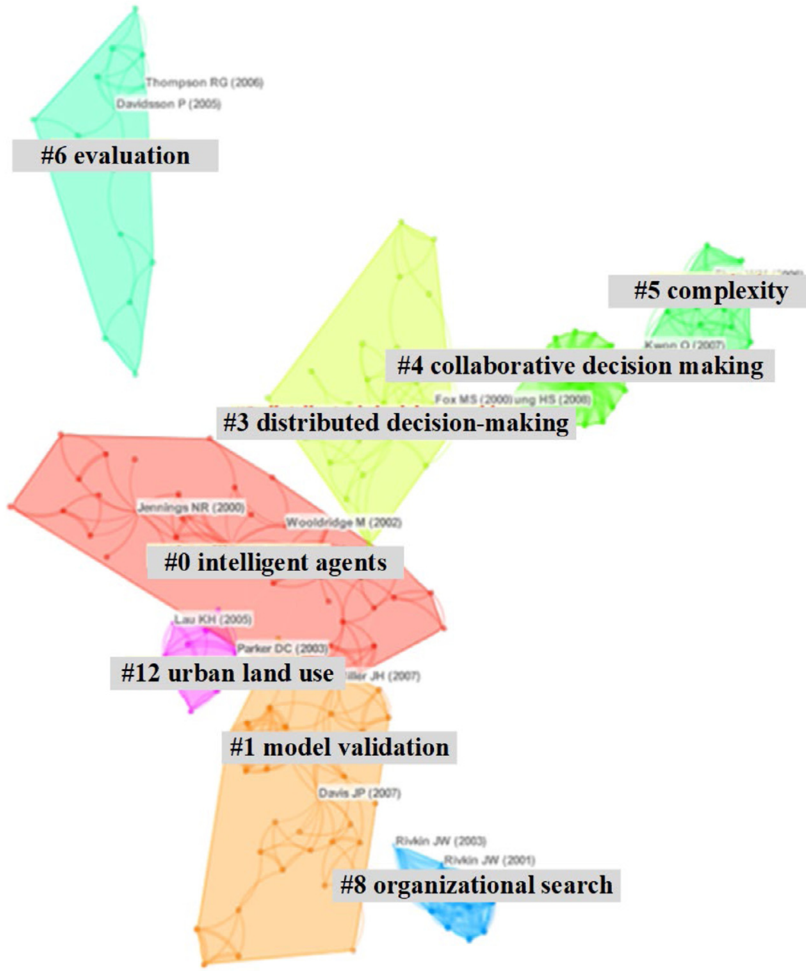

Fig. 8. Research clusters based on the co-citation network.

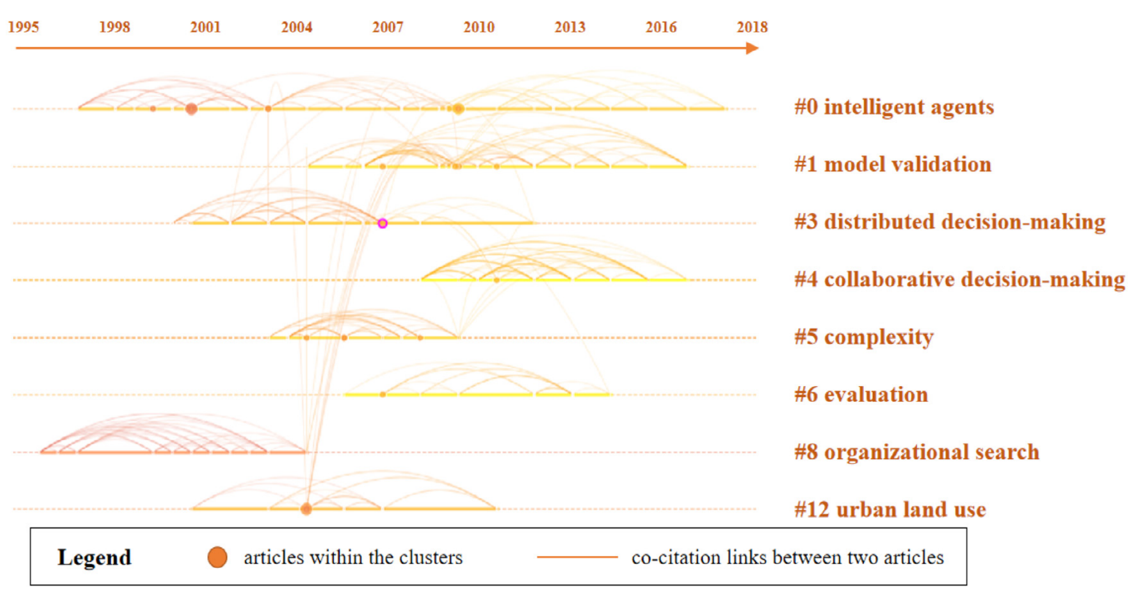

Fig. 9. Timeline of the research clusters.

of the consumer diffusion network is frequently explored in the area of DM-ABM. One of the top themes is the complex environment, indicating its considerable influence on decision-making behaviors. Therefore, the environment is an important factor that must be considered when developing an agent-based model to analyze decision-making issues. Information diversity, firm decisions, and water management were also ranked as top themes in this cluster, revealing that agent-based models have

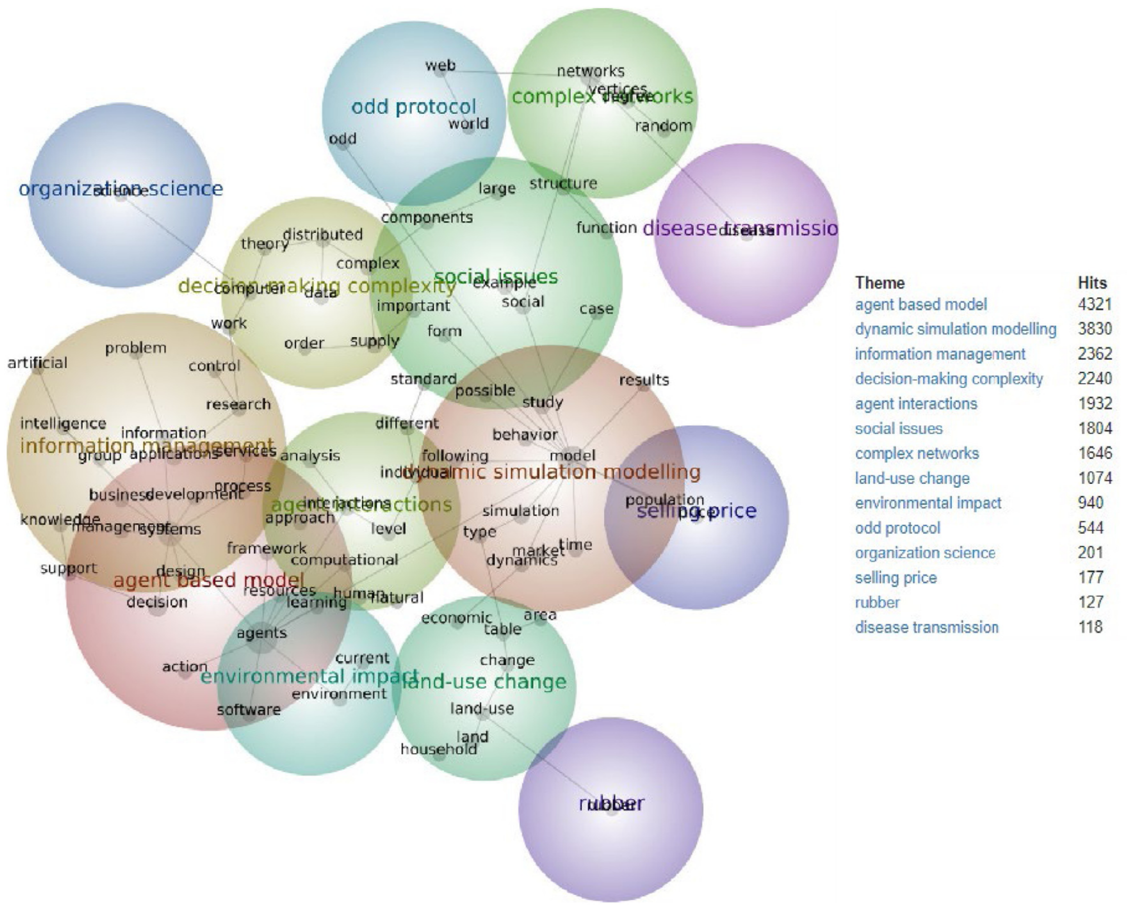

Fig. 10. Knowledge map of the intellectual base of Cluster #0.

frequently been applied to address decision-making issues in these areas.

Cluster #4 collaborative decision making

Compared to the abovementioned two clusters, Cluster #4 is a relatively small group with eight themes. As shown in Fig. 12, several themes in this cluster are associated with supply chain management issues, which indicates that collaborative decision making in supply chains has become an increasingly important topic in recent years. This finding is consistent with many studies that focus on the collaboration of actors from upstream and downstream supply chains to ensure smooth decision making. Supply chain planning is the most frequently discussed theme in this cluster, with up to 2029 hits, whereas production and logistics processes also have over 2000 hits in the texts. Supplier relationships and supply chain performance are two other dominant themes with high academic attention. Although considerable effort has been devoted to decision-making issues in supply chains, this area needs further exploration because supply chains have complex environments with multiple actors whose aims are to maximize the benefits of their own organizations instead of the whole supply chain. Other important topics in this cluster are enterprise integration, IT implementation, and optimal solutions.

4. Future research directions

Because the analysis of knowledge evolution and frontiers is typically based on historical research, the latest studies are relatively overlooked. To identify future research directions, we searched and analyzed studies published from 2019 to 2021 and summarized three future research directions.

4.1. Advanced intelligence of agents

Intelligent agents have been an important research field in ABM in recent decades [56,57]. As shown by the research clusters in Fig. 8, the cluster of intelligent agents has been the No. 1 cluster in recent years, with the largest number of relevant studies, longest duration, and most active areas. In addition, intelligent agents are an important part of the research frontiers of studies of DM-ABM because the agent is the foundation of ABM, and improving its intelligence can enhance the accuracy and efficiency of ABM. Therefore, advanced intelligence of agents is considered an important direction for future research [58].

Learning ability is an important aspect of an agent's intelligence. Traditional studies mainly rely on the manual setting of an agent's learning functions, whereas current research typically uses machine learning algorithms to learn experience and optimize agents' behaviors. Machine learning algorithms can be divided into three main categories: supervised, unsupervised, and reinforcement learning. There is no label (only reward) in reinforcement learning, which is the main difference between the two machine-learning algorithms. Reinforcement learning is closer to human learning, and has been a hot research topic in recent years [59–61]. Learning algorithms can also be integrated with other methods for modeling decision-making behavior, such as neurocognitive architecture, brain science, and behavioral science, in future research [62].

Another important direction for improving agent intelligence is natural language processing. The traditional approach to building an agent's function is mainly based on qualitative field interviews. This empirical approach successfully incorporates an agent's heterogeneous preferences and decision mechanisms [63].

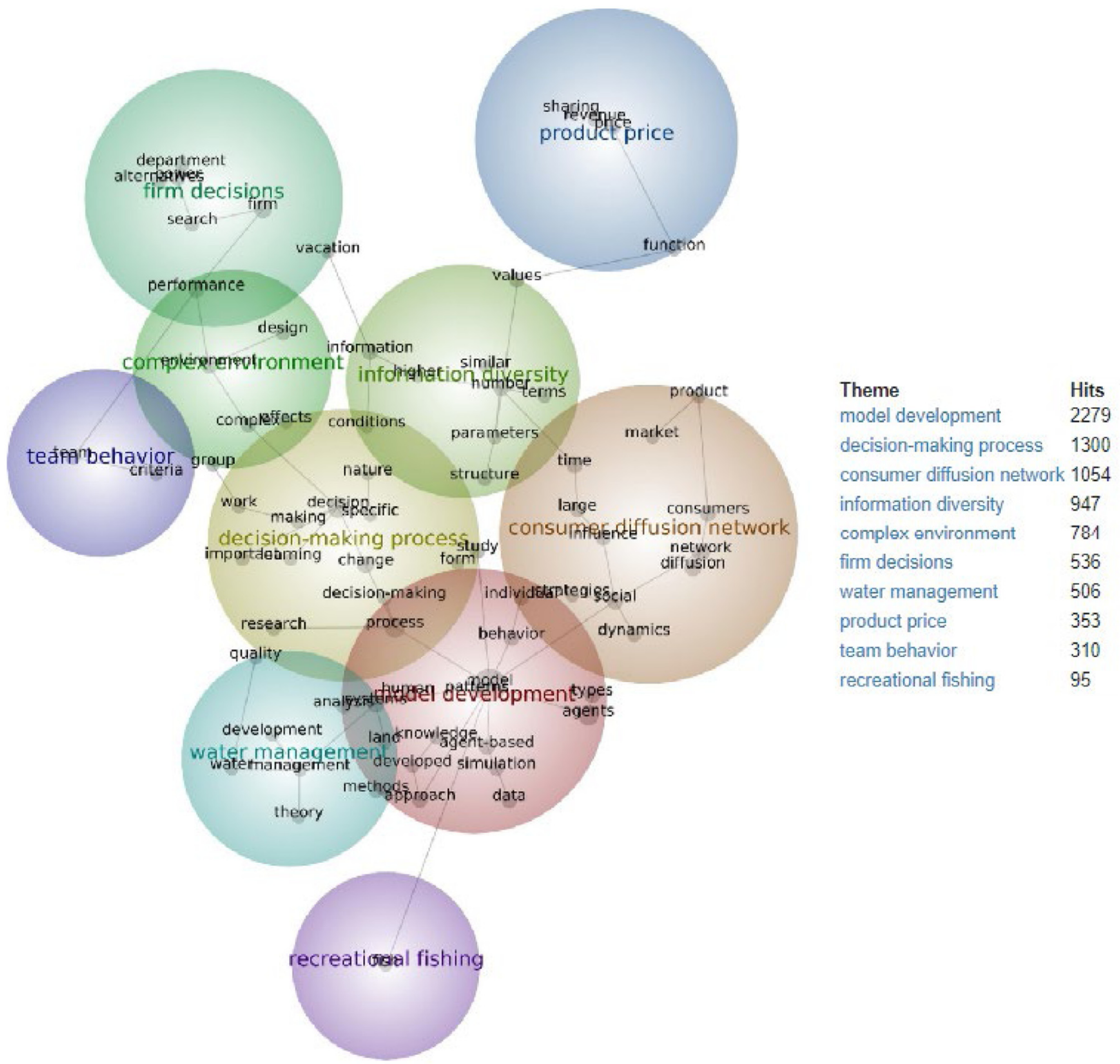

Fig. 11. Knowledge map of the intellectual base of Cluster #1.

However, these approaches are labor-intensive and difficult to replicate, thereby limiting the application of the DM-ABM. Natural language processing, which can use text to capture and represent human cognition automatically, is a potential method to address this problem [64]. Therefore, it can offer a more efficient way to model agents' cognitive processes and build large agent-based models in future studies.

4.2. Approach to reality

Another trend in ABM research is the models' approach to reality, including theories, methods, mechanisms, and variables. Fuzzy decision making is a decision model that is similar to human cognition. For example, three-way decision theory models the actual decision-making process in which people can immediately make quick judgments about matters that they have full confidence in accepting or rejecting; however, for matters that cannot be decided upon immediately, people tend to postpone their judgment [65]. This method has been applied to probabilistic rough sets. These fuzzy decision-making methods can achieve consensus over conflicts and make the decision-making mechanism closer to that of humans [66]. Therefore, this is a major direction for future research.

In addition to fuzzy decision making, irrational decision making is another main direction of recent decision-making research. Traditional decision-making research is generally based on the assumption that a rational individual makes decisions based on the principle of maximizing benefits. In fact, human decision making is not fully rational and can be affected by numerous irrational factors such as emotion and perception. Rzeszutek et al. [67] constructed an agent-based model to explore whether the overconfidence of senior corporate managers in the context of their initial public offering decisions is detrimental for firms. Wolf et al. [68] conducted an ABM study on how emotions affect decisions to purchase decisions. Hyun et al. [69] analyzed the role of risk perception in water management decisions. Ureña et al. (2019) summarized how trust propagation and opinion dynamics influence group decisions. In future research, irrational factors are expected to attract more attention for modeling decision-making behaviors [70].

In addition, more characteristics of agents are included in agent-based models to make the system more realistic, which is a trend in decision-making research. At the individual level, the heterogeneous needs, preferences, and motivations of stakeholders are considered in decision making [63,68]. At the group level, social networks have become a key factor in illustrating the relationships and interactions between agents [70,71]. At the

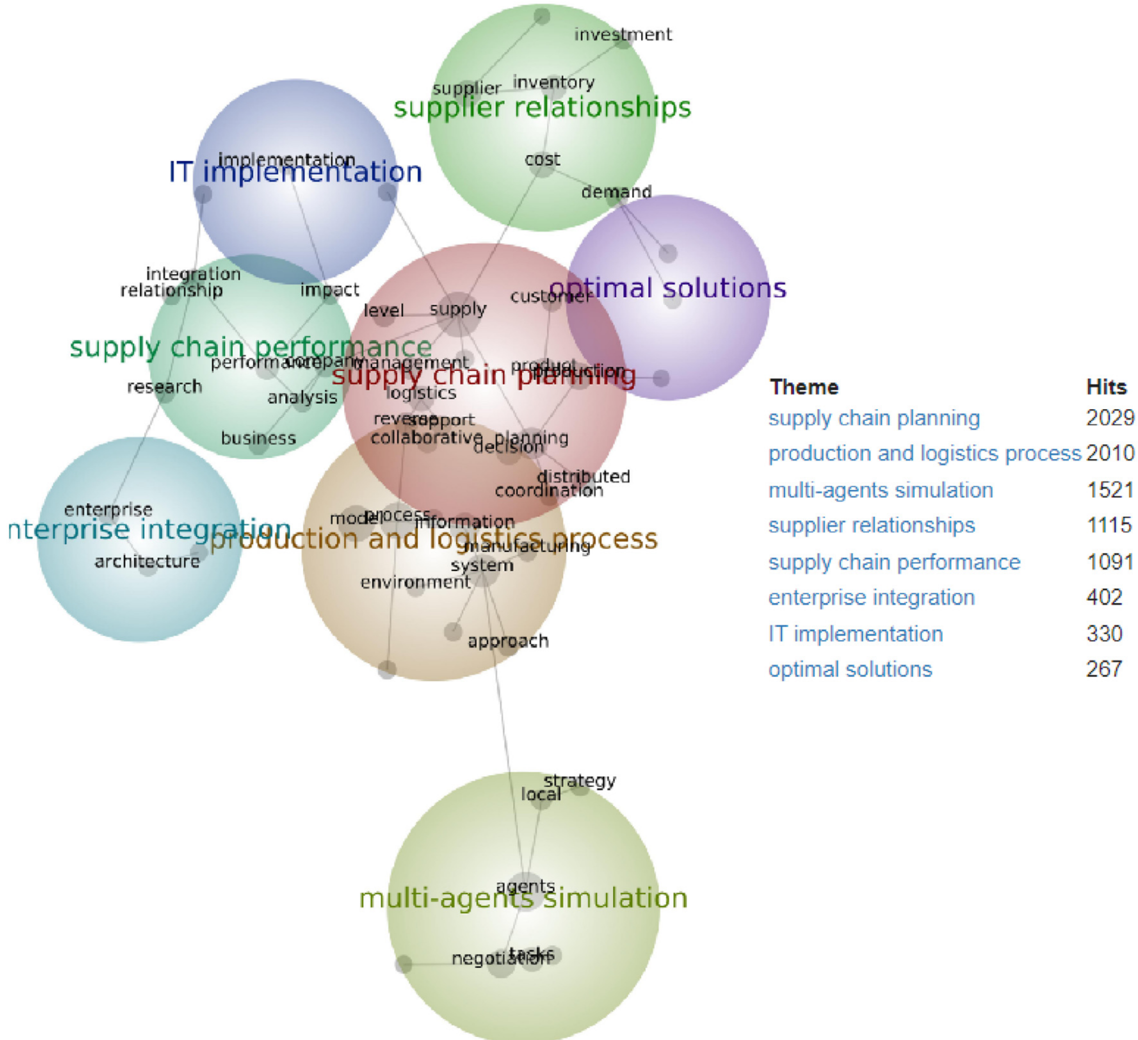

Fig. 12. Knowledge map of the intellectual base of Cluster #4.

system level, the development of more dynamic, adaptive, and complex models is a research trend in ABM that will progress in the future [72].

4.3. Group decision making

Group decision making has attracted significant attention in recent years. Enabling a group to make decisions quickly, efficiently, and accurately is important and difficult when solving practical problems, especially in certain scenarios such as decision making by large groups in emergencies [73]. Several studies have developed group-decision-making methods. For example, Elsenbroich and Payette [74] modeled the cooperation of agents in the dilemma of a public goods game based on the theory of team reasoning. Carneiro et al. [75] proposed a web-based group decision support system based on an argumentation dialog model. Han et al. [76] applied interval-valued Pythagorean fuzzy sets to solve a multi-criteria group decision-making problem.

The conflict and consensus problem is the main challenge in group decision making. In most MASs, a number of agents with various characteristics and interests must reach consensus and make common decisions [77]. However, agents are autonomous and lack a global perspective or sufficient data to automatically reach a consensus [78]. Some studies have developed novel methods for improving the consensus of agents, including collaborative frameworks, interrelations, and assessments [79,80]. In future studies, advanced algorithms and mechanisms to resolve conflicts and facilitate consensus are required for the DM-ABM.

4.4. Innovative modeling methodologies and diversified applications

Agent-oriented software engineering (AOSE) is a software paradigm for developing complex MAS by focusing on the use and organization of agents as the main abstractions. It can be applied to the entire lifecycle of software development and can help build models systematically and rapidly [81]. Previous studies have proposed various AOSE-related methodologies (e.g., KAOS, Kendall, TROPOS) from different perspectives, including agent theory, object-oriented systems, and knowledge-based systems [82–84]. New methodologies have been continuously developed and updated. For example, the GRASIA research group designed a methodology named INGENIAS, which adopts engineering concepts to support multiple stages of software development and is therefore friendly to end users [85,86]. Recently, hybrid simulation methods and models have been developed and validated, which is a potential research frontier [87].

Based on innovations in methodologies, the number of applications of MAS has been increasing in different areas, including transportation, environment, agriculture, decision making, supply chain, and public policy [53,63,68,88,89]. For example, Fernández-Isabel et al. [89] proposed an MAS to simulate road traffic with specific elements for smart roads (e.g., sensors and services). Cabezas et al. [90] presented a bio-inspired MAS for automatically detecting fraudulent websites based on the INGENIAS methodology. Cares et al. [91] described the suitability of AOSE for developing cyber–physical systems and illustrated several examples based on TROPOS. In recent years, various applications of MAS have been developed, which are expanding the research frontiers.

5. Conclusions and implications

Decision making has long been an important topic in management science and operational management research. Numerous studies have examined decision-making issues over the past two decades, and the application of ABM has received increasing attention owing to its manifold technological advantages over other methods. This study comprehensively reviewed relevant decision-making studies using ABM. Keyword search was conducted in the Web of Science Core Collection dataset to collect literature information on the most relevant studies in this field for the analysis. Bibliometric mapping and text mining are then combined to explore the knowledge frontiers and evolution of research on DM-ABM.

First, the knowledge networks of the studies were mapped using CiteSpace. The relationship between citations and cited citations is provided to demonstrate the relationship network of studies in different categories. Intellectual milestones were also identified using DCA to determine the most highly cited papers and their relationships.

Second, knowledge frontiers were identified by analyzing the research clusters of the studies. The eight largest clusters were identified using co-citation cohesiveness analysis. The three largest and hottest clusters were considered frontier areas for further analysis. Text mining was then conducted to analyze the full texts of studies in each frontier area in depth to identify the critical themes and their connections.

Third, knowledge evolution was analyzed from multiple perspectives. The development of keywords over time has been mapped to show the four major waves of recent decades. Then, six groups in which keywords with high concurrence were included were summarized and analyzed to explore the evolution of topics over time. A citation burst was then conducted to identify critical research in each period. These studies play critical mediating roles in knowledge evolution and are analyzed as transition points.

Considering that the above analysis of knowledge evolution and frontiers is based on historical research with little reflection on the most recent studies, this study also investigates the recent literature and proposes three future research directions: advanced intelligence of agents, approach to reality, group decision making, and innovative modeling methodologies and diversified applications. Thus, this study bridges existing knowledge gaps by comprehensively reviewing research on DM-ABM to identify the most critical studies in the knowledge network and to show the trend of knowledge development over time. However, this study places little emphasis on mathematical models or solution methods to solve decision-making problems, and this limitation should be addressed in future research.

CRediT authorship contribution statement

Xin Liang: Conceptualization, Methodology, Writing – review & editing, Funding acquisition. **Lizi Luo:** Formal analysis, Writing – original draft, Funding acquisition. **Shiying Hu:** Discussions. **Yuke Li:** Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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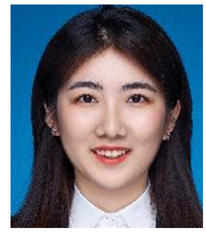

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