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An integrated latent Dirichlet allocation and Word2vec method for generating the topic evolution of mental models from global to local

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ABSTRACT

Mental models play a crucial role in explaining and driving human innovation activities. To help researchers clarify the changes of mental models in various innovation situations, an exploration of its topic dynamic evolution changes is urgently needed. However, most existing works have discussed the topic-semantic distributions of collected documents along the overall timeline, which ignores the semantic details of fusion and evolution between topics in continuous time. This paper discovers and reveals the multi-level information evolving of topics, by integrating latent Dirichlet allocation (LDA) and Word2vec harmoniously to generate the topic evolution maps of the corpus from global to local perspectives. Which include topic distribution trends and their dynamic evolution under the overall time series, as well as the merging and splitting of semantic information between topics in the adjacent time span. These reveal the correlation between topics and the full life cycle of a topic emerging, developing, maturing, and fading. Then, the integrated method was used to perform an analysis of topic evolution with 3984 abstracts of mental model-related papers published between 1980 and 2020. Finally, the performance of the proposed method was compared to that of three traditional topic evolution generated methods based on the standard evaluation metrics. The experimental results demonstrated that our method outperforms other methods both in terms of the content and strength of topic evolution. The proposed method could mine the latent evolution information more clearly and comprehensively from a vast number of papers and is also suited to the various applications of expert systems related to information mining works.

1. Introduction

The term mental models was first used by the psychologist (Craik, 1943) and refers to a mental mechanism whereby humans generate descriptions of system purpose and form, explanations of system functioning and observed system states, and predictions of the future of system states (Rouse & Morris, 1985). With today's world becoming ever more interconnected and dynamic, innovations that are highly dependent on human activities occurring at increasing rates in all pertinent areas of life have significant impacts. However, the performance of these activities is based on feedback, adaptation, and subsequent learning, which is guided by human mental models (Groesser & Schaffernicht, 2012). Mental models can allow people to draw inferences, make predictions, understand phenomena, decide which actions to take, and experience events vicariously (Johnson-Laird). The development of mental models has generated several application situations according to various innovation activities, such as the mental models of dynamic systems (Doyle & Ford, 1998; Schaffernicht & Groesser, 2011; Scholz et al., 2015), the shared mental models of team cooperation (Langan-Fox et al., 2004; Marshall, 2007) and the user mental models of interactive design (Casakin & Badke-Schaub, 2017; Sax & Clack, 2015; Vink et al., 2019). In addition, human mental health and the conception of the internal mental state also played a central role in psychology (Majid, 2020; McComb & Simpson, 2014) and information science (Zhang, 2008, 2013), respectively. With the evolution of innovation activities, the application and expression of mental models have emerged as a new kind of developed trend. These trends can both feedback and motivate human decision-making activities, and thus, it is vitally important to explore trends in mental models.

However, existing studies have primarily focused on the construction and application of mental models, with few systematic analyses

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and subsequent collations regarding its development, making it imperative to perform a comprehensive and in-depth analysis of mental models. However, the large number of online mental model-related publications makes it impossible to gain an overview of this field. Topic evolution mining based on the massive text in natural language processing solves this problem and has been widely applied in many studies, such as emerging topic detection (Huang et al., 2021), crisis management (Deng et al., 2018, 2020), and technology prediction (Bai et al., 2021; Chen et al., 2020b). This can indicate the topic's changing trends with a continuous timeline, including the emergence, developing, readjusting, maturation and fading status of topics, as well as the knowledge transfer between topics. Thus, constructing a topic evolution helps us to capture characteristics such as topic development trends and the details of information migration.

In recent years, to effectively capture the character of topic evolution for sequentially organized publications with time, topic models that incorporate timestamps have been developed. Among them, latent Dirichlet allocation (LDA) (Blei et al., 2003) and probabilistic latent semantic analysis (PLSA) (Hofmann, 2004) are the two most conventional topic evolution construction models, both representing articles as a mixture of topics and each topic as the probability distribution over words and being widely applied to modeling the topics of multiple fields, such as information retrieval (Chen et al., 2017), 3-D printing technology (Chen et al., 2020a; Miao et al., 2020), consumer complaints (Bastani et al., 2019) and cross-media (Zhou et al., 2017). Blei and Lafferty (2006) and Mei and Zhai (2005), respectively. TTM is considered to uncover temporal patterns in text information that has been collected over time, and DTM considers the time evolution factor between neighboring time slices. However, these models obtain a chain-like topic evolution path by evaluating the topic distribution within different periods. They mainly focus on the content changes of a topic and fail to consider the dynamic changes of correlations between topics.

For clarity, more details of the document information during the process of topic evolution and models that incorporate timestamps have been developed.(Wang & McCallum, 2006) proposed the topic over time (ToT), a model that first jointly models both word co-occurrences and timestamps in a probabilistic topic model. In their study, the timestamps are generated by a per-topic β distribution instead of using the publication date of articles, and a topic is represented as a multinomial distribution of words. Similarly, Zhu et al. (2015) proposed a coherent topic hierarchy (CTH) to explore the topic evolution of microblog feeds with presented local topics in merging and splitting flows under a continuous timeline. Chen et al. (2015) designed a framework to effectively describe the merging, developing, fading of topics for timely event analysis. However, all these continuous-time topic evolution models fail to consider the correlation between topics at the same time span. This makes it difficult for readers to understand the interconnection between correlated topics and the whole evolution quickly (Gao et al., 2019).

Overall, we divide the research methods on the topic evolution into two main directions. One is to describe the information evolution within a topic and the topic evolution between adjacent times, such as DTM, TTM, and their derived models, such as multiscale topic tomography (MTTM) (Nallapati et al., 2007) and infinite dynamic topic model (iDTM) (Ahmed & Xing, 2008), but these types of methods only focus on the evolution within the same topic, ignoring the evolution of the correlation strength between the topics. The second type, such as ToT and CTH, generate the topic evolution based on continuous time but ignore the change process among topics between different time slices.

In addition, the mentioned probability-based topic evolution modeling techniques fail to capture the entire context of the document because they usually use a unigram representation that considers a word independently (Yue & Zhai, 2008) and ignore the fact that words in different contexts should have different probability weight distributions. Accordingly, Word2vec solves this problem by quantifying the word into a vector by considering the contextual information (Mikolov et al., 2013). This distinguishes the same words from different documents. In other words, a word expresses different semantic information within different contexts. Exploring knowledge transfer between topics is also a neglected method. Many word2vec-based approaches have emerged in natural language processing. Examples include combining LDA and word2vec in technology forecasting from patents (Kwon et al., 2022), polarity detection from review text (Truică et al., 2021), and employing LDA and Word2vec to enhance the recommendation system based on user's historical data (Lei et al., 2020). In the studies of topic evolution, there are also numerous methods for topic evolution analysis based on word2vec. Moody (2016) and Gao et al. (2022) combined DTM and Word2vec to yield topics by capturing token semantic and syntactic regularities in language. Hu et al. (2019) used the Google Word2vec model and spatial autocorrelation analysis to develop semantic spaces such as an urban geographic space. Huang et al. (2022) applied Word2vec and piecewise linear representation to generate a framework for topic evolution with time-series segmentation.

However, existing research on topic evolution has focused on how to achieve a single level of semantic information about topic distributions and topic words without further exploring evolutionary details, such as the details of semantic changes of tokens in each topic and neighboring topics. For topic evolution, we need to not only consider topic distribution but also emphasize the process of evolutionary details among topics. Therefore, in this paper, we apply LDA and Word2vec to topic evolution analysis, fully considering the dual advantages of the probability-based topic model and word embedding representation and avoiding the noncontextuality and sparsity of the topic model. On this basis, we acquired information about the topic evolution from the macroscopic level and further explored the details of semantic migration between topics from the microscopic level, which helped researchers obtain more comprehensive and multidimensional information on topic evolution.

Our contributions and the main contributions of this paper are summarized as follows:

- We proposed a novel approach to extracting the vector space of topics, which combines probability-based topic modeling and textual embedding while fully considering the topic's word contextual information in documents. Every topic word and its weights that were extracted from the LDA were vectorized by Word2vec, and then we used the cosine similarity to calculate the correlation to represent the knowledge transfer between topics in a global time or different time span.
- According to the timeline of collected documents, we constructed the process of topic dynamic evolution based on overall time and part-time to reveal the information changes of topics from the macro/global level to the micro/local level. Including global topic trend detection and dynamic evolution discovered overall continuous time, and the merging and splitting of topics are also presented by the correlation of topics in the adjacent periods. The words 'semantic information was further used to help us to truly understand the meaning of topics rather than labeling them manually.
- This approach was applied to mental model-related documents and generated a comprehensive understanding of topic dynamic evolution analysis for mental models. First, a global evolution perspective of mental models was discovered based on all documents. Then, we discussed the details about information transfer between topics of mental models. This helps scholars who conduct related research have a global understanding and prediction of their studies.
- Based on real text data related to mental models, we compared the performance of the proposed method with that of conventional topic evolution methods. The experimental results show that our method can produce stronger coherence of global topics

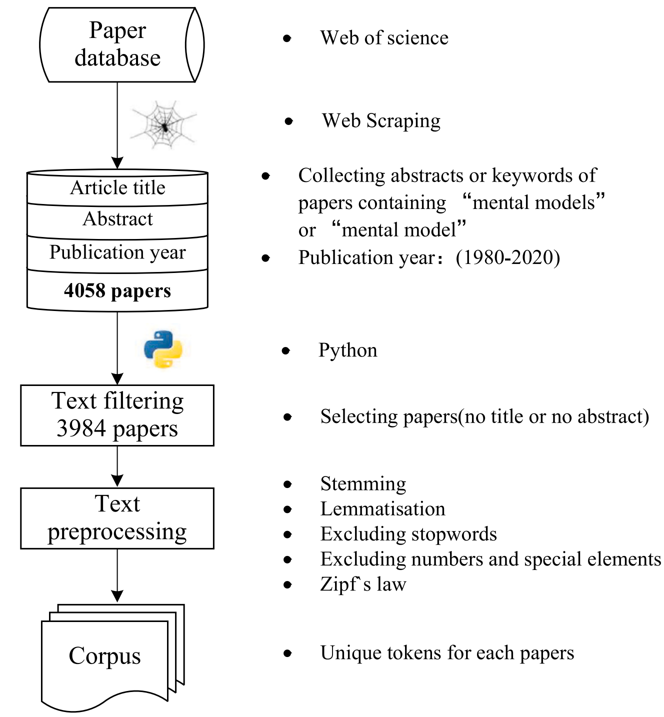


Fig. 1. Data collecting and processing.

and high topic intensity of local topics, which was founded by the topic coherence measure and topic word average similarity score, respectively. In addition, this paper aims to provide an effective and convenient method to capture the dynamic evolution of information. It can also be applicable for some other fields of information evolution analysis but is not limited to mental models.

The rest of the paper is organized as follows: Section 2 describes the work of data collection and processing. A novel constructing method of topic dynamic evolution is proposed and detailed in Section 3. Sections 4 and 5 present the topic evolution result and its quantitative comparison with the conventional methods. Finally, Section 6 concludes this paper and discusses the limitations and further work.

2. Data collection and processing

2.1. Data collection and processing

In this research, mental models are chosen as the target domain. Fig. 1 shows the process of data collection and processing used to conduct topic modeling about mental models. For mental model topic evolution trend analysis, we collected papers from Web of Science for 1980–2020, making a total of 4058 papers, whose keywords or abstracts contain words such as "mental models", "mental model" or "mental models". In this case, the article types were confined to "Articles", and the languages were confined to "English". To ensure the accuracy of the information in the corpus for topic modeling, papers with no title or no abstract were removed. Fig. 2 represents the number of final selected papers published per year with a total of 3984.

The abstracts in the article were used for analysis. Before conducting the topic evolution modeling, the abstracts of the final selected papers were collected for processing. (1) Special elements, such as numbers, punctuation, and symbols, were excluded. (2) The abbreviations of the abstract were standardized to eliminate duplicate references to the same concept. For instance, "MMs" and "mental models"; "SMM" and "shared mental models"; "TMM" and "team mental models". (3)

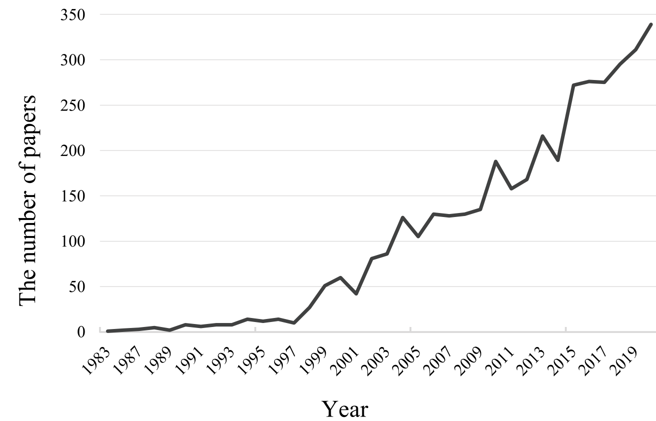


Fig. 2. Number of papers.

Convert words of the abstract to lowercase, basic verbs, stop words, and some special words such as 'mental', 'model', 'models', and 'mental-model' were also excluded, which are meaningless in the topic evolution trend analysis. (4) Stemming and lemmatization. (5) Employed Zipf's Law to remove words that were either too common or too rare. Finally, we obtained a corpus with unique tokens in each article and extracted a total of 13,735 unique tokens from it.

3. Methodology

3.1. Latent Dirichlet allocation

Latent Dirichlet allocation (LDA) was first developed by Blei et al. (2003) and is applied to reveal the hidden semantic structure of the corpus. LDA is a three-layer Bayesian model that is now widely used to discover latent topic themes in a collection of documents. The main idea is that each document exhibits a mixture of latent topics wherein each topic is characterized by a probability distribution over the words (unique tokens for the collection of documents). The generative process of LDA is represented in Fig. 3. Among them, K denotes the number of topics, M denotes the number of collected articles and N_m denotes the total number words of article m. For each topic, a topic word distribution ϕ_k is generated. For each collected article m,a topic distribution θ_m is generated. In addition, $Z_{(m,n)}$ indicates the topic assignment of the nth word in the mth article, and $W_{(m,n)}$ indicates the nth word in the mth article. α and β are two user-defined hyperparameters to determine the smoothing for ϕ_k and θ_m respectively. A more detailed explanation of the algorithm can be found in Blei (2012).

3.2. Word2vec

Word2vec as a neural language model was first proposed by Mikolov et al. (2013) to represent words in a corpus as a vector with contextual comprehension. There are two model architectures of word2vec: continuous bag-of-words (CBOW) and skip-grams (SG). The main difference between those two types is that SG uses the center word to predict the probability distribution of surrounding words, whereas CBOW gives us a predicted probability distribution of nearby words by inputting a center word. For the Word2vec model, there are also two efficiency optimization techniques being applied: hierarchical softmax and negative sampling. Both tricks optimize only the computation of the updates for output vectors, the former considering all output vectors (Rong, 2014), whereas the latter considers a sample of them.

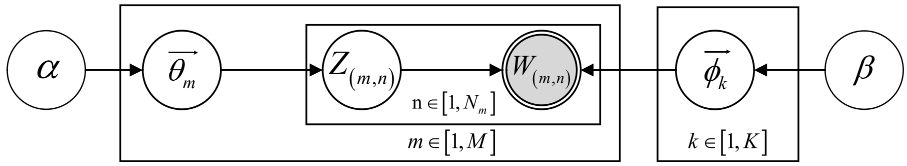


Fig. 3. Illustration of the LDA generative process.

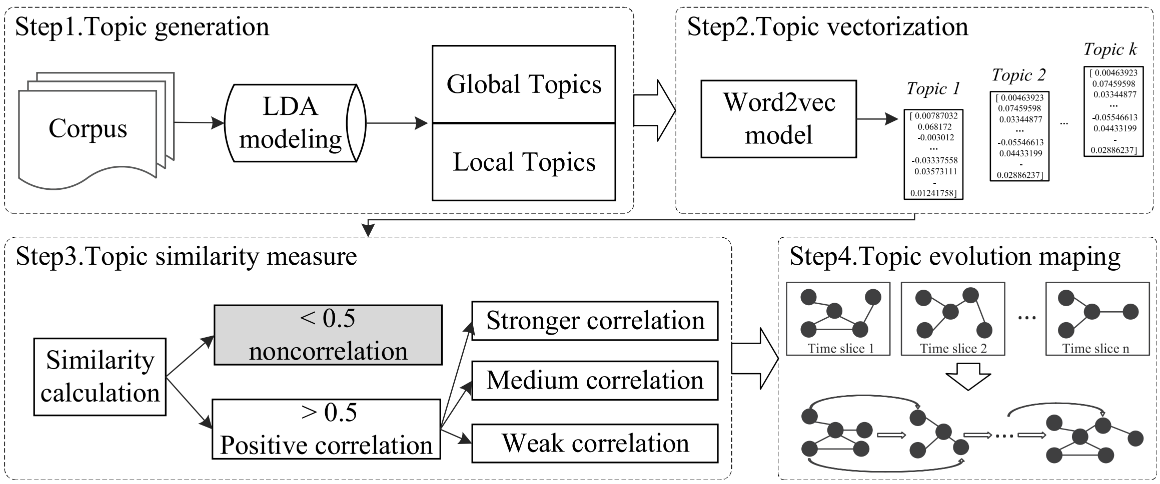


Fig. 4. The main steps of proposed topic evolution mapping method.

3.3. Proposed methodology

To better describe the evolution path of the mental models from a macro level to a detail level. In this paper, we propose a new method combining LDA and word2vec to realize topic evolution mapping. Based on the implementation of the probabilistic statistical model, the corpus context relationship is also fully considered to effectively improve the quality of document topic modeling and the accuracy of the topic evolution process. Fig. 4 illustrates the main steps of our proposed approach. The details of each step are explained as follows.

Step 1: Topic generation. According to time division, LDA processing is performed on the preprocessed corpus to generate two types of topics, global and local. Global topics are topics extracted from the total corpus to represent the overall information of related work; local topics are topics extracted from the corpus of each time slice to represent the detailed information of specific periods.

Step 2: Topic vectorization. In this process, the abstract texts of article records are used as the input to construct the mathematical vectors for each topic. More details of this step are further explained in Fig. 5.

Word2vec, as the neuro language model, takes topic words as the input and the context in the sentences from the abstract texts as the output. After model training, the Word2vec model can be obtained and each keyword from the global/local topics is represented as the high-dimensional vector space through the Word2vec model. Then, each word vector a_{mi} and its weight w_{mi} in each topic are weighted and summed to obtain the final topic vectors. The calculation formula is as follows:

$$Topic_{vector} = \sum_{i=1}^{n} W_{mi} \cdot a_{mi} \tag{1}$$

Many studies only considers the keywords of extracted topics, but ignore the weight of the word in each topic. This step integrates each word vector and its weight to represent a topic, which can interpret topic information accurately and help us better explore the correlation between different topics.

Step 3: Topics correlation measure. The topic correlation is calculated by cosine similarity (Nasir et al., 2013) between different topics. These are subject to the following distribution:

$$Topic_{correlation} = similarity = \frac{G \cdot L}{\|G\| \, \|L\|} = \frac{\sum_{i=1}^{n} G_i \cdot L_i}{\sqrt{\sum_{i=1}^{n} (G_i)^2} \cdot \sqrt{\sum_{i=1}^{n} (L_i)^2}} \tag{2}$$

Among them, G and L indicate two different topic vectors of global and local topics, respectively. In this way, we obtained the correlation of the local topics at adjacent periods as well as the correlation between global topics and local topics under continuous time. For further clarity of the correlation between topics, three correlation patterns, including “strong correlation”, “medium correlation” and “weak correlation”, are identified in the analysis correlation results. The threshold for judging whether the topic’s correlation is significant or not is set according to the final data results. Often, this threshold is set at 0.5. In this paper, the threshold of positive correlation is set at 0.5.

Step 4: After topic correlation calculation, the topic evolution maps are generated. There are two kinds of information that must be explained before topic evolution maps are generated:

(1) Evolution status of global topics, which is indicated by its correlation with local topics in each time span. The strong correlation indicates a high similarity in vector space between global topics and local topics, and global topics are in a mature status of development at that time. The medium and weak correlation indicates that the global topic is in a developing and readjusting status, respectively, at the time corresponding to the local topic.
(2) Merging and splitting flows represent the transfer process of evolution structure among adjacent local topics. which indicates the interweaving changes of global topic information in the local topics under continuous-time spans.

First, we employed the nodes and connection flows to construct a local topic correlation graph in each time slice. where the nodes represent each local topic in a time slice, and the flows represent the

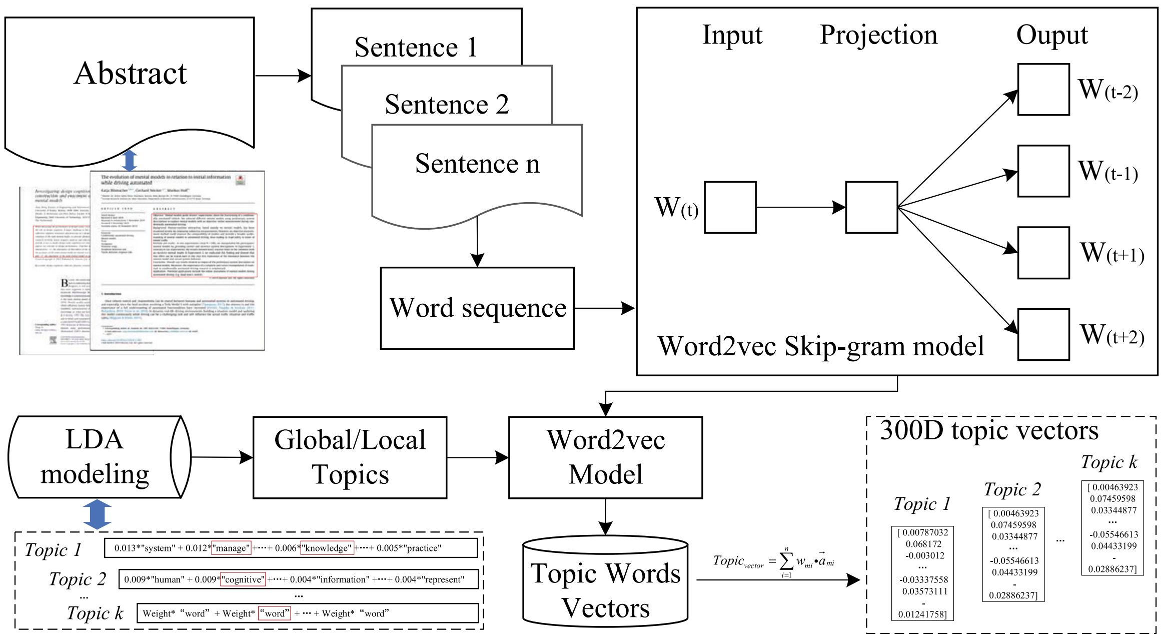


Fig. 5. Overall process of topic vectorization.

intersection and splitting trends based on the topic correlation. Second, the correlation between global topics and local topics in each time slice is calculated to construct global topic evolution maps during the overall continuous time. Meanwhile, all the above topic correlations are distinguished by the threshold of positive correlations to further represent strong, medium, and weak correlations between topics.

4. Result

4.1. LDA modeling

Before topic modeling with LDA, the hyperparameters α and β and topic number K must be predefined. Based on the precedent topic modeling research (Heinrich, 2005; Miao et al., 2020), we set the parameters $\alpha = 50/K$, and $\beta = 0.1$ and used Gibbs sampling to obtain topics. The number of topics K was determined by the perplexity measure (Blei et al., 2003; Chen et al., 2020a; Miao et al., 2020), which indicates the degree of uncertainty of a document belonging to a topic and can be used to evaluate the topic model (Jurafsky & Martin, 2010). The number of topics corresponding to the smaller perplexity was selected as the optimal topic number. The perplexity calculation process was subject to the following equation:

$$perplexity(D) = exp\left(-\frac{\sum_{m=1}^{M} log P(z|m) P(w|z)}{\sum_{m=1}^{M} N_m}\right) \quad (3)$$

where M is the total number of documents; N_m denotes the total number words of document m; $P(z|m)$ denotes the probability of topic z in document m; and $P(w|z)$ is the probability of word w in topic z. However, the global topics are extracted from all collected documents. Many related studies (Bastani et al., 2019; Chen et al., 2017) usually determine the optimal topic numbers by trial or error processes in large-scale documents. In this paper, we employed hierarchical clustering to select the optimal topic numbers of the global topics, and the results are shown in Fig. 6(a). The number of clusters that covered 85% of the overall documents was selected as the optimal number of global topics, and the final selected six global topics were further verified by topic coherence calculation (see Fig. 6(b)).

4.2. Global topic popularity trends detection

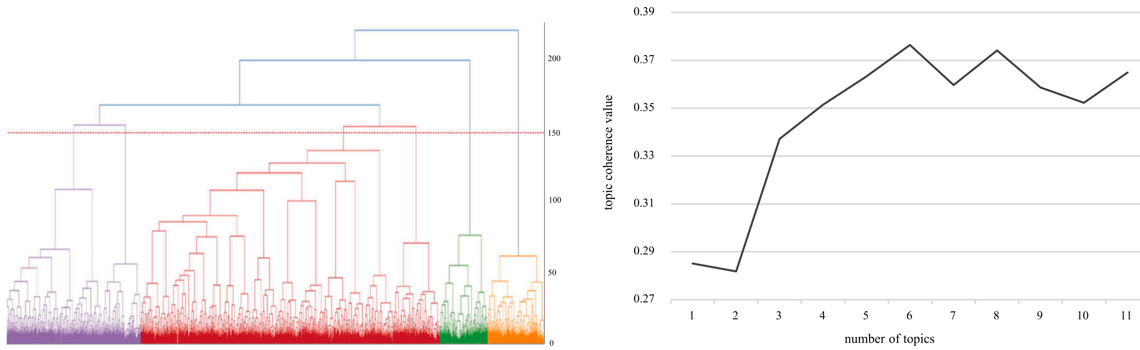
With the massive amount of literature available now, topic trend detection can assist us in obtaining an overview of research theme popularity based on the overall timeline. Many studies (Börner et al., 2003; He et al., 2009; Zhou et al., 2006) have generated topic trends over time by simply counting the numbers in a topic year by year, which ignores the characters wherein one document may contain multiple topics. In this paper, the per-document global topic distribution obtained by topic modeling is applied to generate topic trends over time.

The global topic distribution of each document is aggregated by year. Each document is presented with a probability distribution over the six global topics, which are determined at 4.1. Fig. 7 presents the process of global topic popularity generation in 2018, 2019, and 2020. Each row in the left table indicates one document with a probability distribution of six global topics. Documents are grouped by year, and the probability of the same topic in the same year is summed (Fig. 7 upper-right). Then, the results are normalized by dividing the summed values by the year document sum. (Fig. 7 lower-right). The final results show that all six global topics are fluctuate around the probability value of 0.16 every year, which makes sense $0.16 \approx 1/6$.

4.3. Topic evolution dynamic discovery

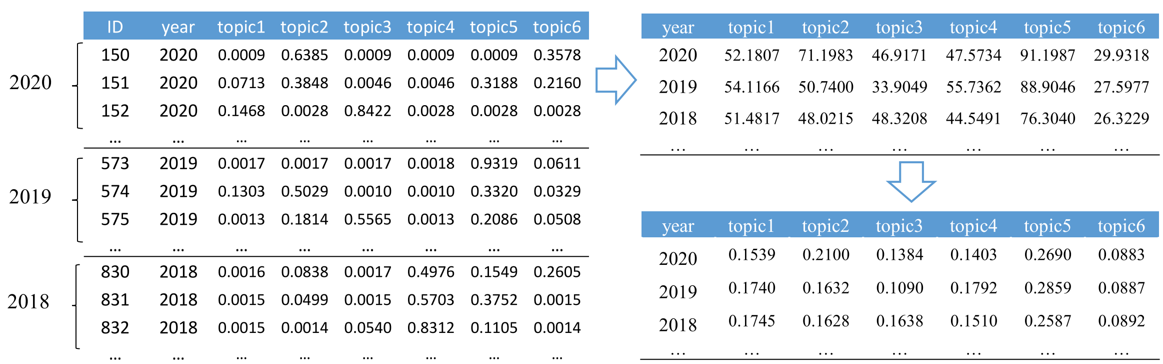
The topic evolution dynamic discovery included the merging and splitting of the topic information. We employed LDA and Word2vec to obtain local topic vectors in the documents for each year. The correlation of the local topics calculated by topic vector similarity in adjacent time. Each node represents the local topic in a specific year, and the flows represent the correlation between local topics in an adjacent year.

In this paper, we divided the entire corpus into six-time slices with a five-year interval:198–1995, 1996–2000, 2001–2005, 2005–2010, 2011–2015, and 2016–2020 because it is inconvenient to analyze the per-year topic evolution of we selected from 1980 to 2020. Then we employed LDA and Word2vec to obtain local topic vectors in the documents for each time span. The optimal number of topics in each period was determined by the perplexity measure, as shown in Fig. 8.



(a) Hierarchical clustering (b) Topic coherence evaluation

Fig. 6. Hierarchical clustering and topic coherence evaluation.



	ID	year	topic1	topic2	topic3	topic4	topic5	topic6
2020	150	2020	0.0009	0.6385	0.0009	0.0009	0.0009	0.3578
	151	2020	0.0713	0.3848	0.0046	0.0046	0.3188	0.2160
	152	2020	0.1468	0.0028	0.8422	0.0028	0.0028	0.0028
	...	...	...	...	...	...	...	...
2019	573	2019	0.0017	0.0017	0.0017	0.0018	0.9319	0.0611
	574	2019	0.1303	0.5029	0.0010	0.0010	0.3320	0.0329
	575	2019	0.0013	0.1814	0.5565	0.0013	0.2086	0.0508
	...	...	...	...	...	...	...	...
2018	830	2018	0.0016	0.0838	0.0017	0.4976	0.1549	0.2605
	831	2018	0.0015	0.0499	0.0015	0.5703	0.3752	0.0015
	832	2018	0.0015	0.0014	0.0540	0.8312	0.1105	0.0014
	...	...	...	...	...	...	...	...

year	topic1	topic2	topic3	topic4	topic5	topic6
2020	52.1807	71.1983	46.9171	47.5734	91.1987	29.9318
2019	54.1166	50.7400	33.9049	55.7362	88.9046	27.5977
2018	51.4817	48.0215	48.3208	44.5491	76.3040	26.3229
…	…	…	…	…	…	…

year	topic1	topic2	topic3	topic4	topic5	topic6
2020	0.1539	0.2100	0.1384	0.1403	0.2690	0.0883
2019	0.1740	0.1632	0.1090	0.1792	0.2859	0.0887
2018	0.1745	0.1628	0.1638	0.1510	0.2587	0.0892
…	…	…	…	…	…	…

Fig. 7. The process of global topic popularity generation.

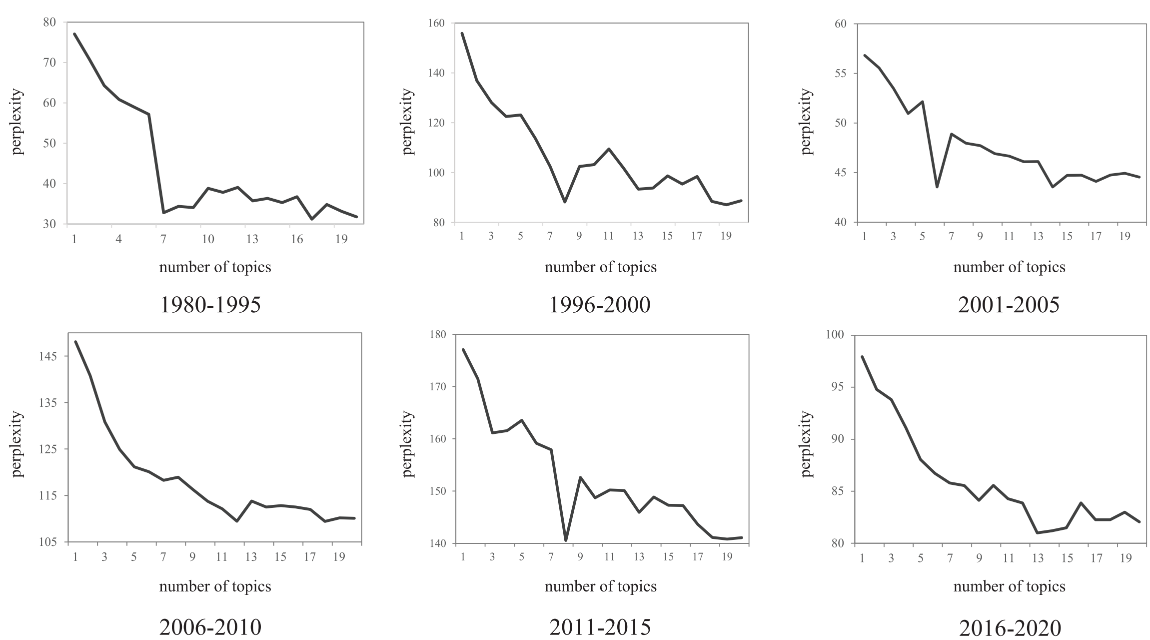


Fig. 8. The optimal number of topics of each time span calculated by perplexity measure.

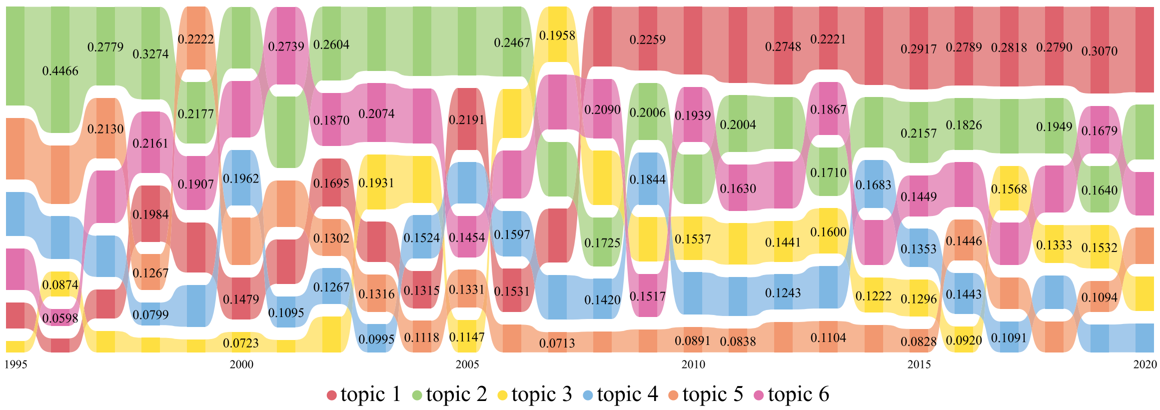


Fig. 9. Global topics popularity trends.

Table 1
Top words of global topics.

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6
system	human	student	team	patient	learn
mange	cognitive	study	share	care	user
develop	theory	concept	effect	condition	design
use	system	learn	perform	reason	use
research	reason	use	task	theory	study
approach	use	child	study	use	information
decide	process	knowledge	text	conclusion	develop
study	base	understand	process	result	base
change	experience	educate	spatial	nurse	effect
risk	situation	teacher	result	experiment	research

5. Discussion

5.1. Global topic popularity trends

Table 1 presents the top 15 words with high probabilities of the global topics. We obtain an overview of the mental model research distribution with these topics and words. Fig. 9 shows the popularity trends of all global topics, which were generated in Section 4.2. The width and position of the flow are used to reflect a topic's popularity, where the wider or closer to the top of the flow, the more popular the topic.

As shown in Fig. 9, the six global topic changing tendencies are quite different in each time span. In general, global topic 2 and global topic 5 have a shrinking or declining tendency, whereas global topic 1 has a sharply growing tendency. Global topic 3 has the most fluctuating tendency among these six global topics. Global topic 1 (system & management) was at the lowest level before 1996; after experiencing constant fluctuations, it began to sharply expand and reached its peak in 2008. Global topic 2 (human cognitive) dominated at the beginning. However, suddenly shrinking reached the lowest state in 2008, gained high popularity and remained approximately stable soon thereafter. Global topic 3 (student & education) remained at the lowest level approximately 2000 and then gradually expanded, reaching the peak, while global topic 2 shrunk approximately 2008. Global topic 4 (team share) remains at a medium level, and gained more popularity in 2000, 2005, 2009, and 2014. Global topic 5 (mental health) peaked in 1999 and suddenly lost popularity in the following years, reaching minimum approximately 2005. Global topic 6 (design study) peaked in 2001 and started declining and experienced constant fluctuations thereafter.

5.2. Topic evolution dynamic

In this part, for clarity of the three patterns of positive correlation that have inter-topic vector similarity values above 0.5, we used three different colors to label those patterns, including strong correlation (red), medium correlation (blue), and weak correlation (green). The final similarity intervals are set as (0.6,0.75], (0.75,0.85], and (0.85,1], referring to strong correlation, medium correlation, and weak correlation, respectively. The above intervals are determined by our similarity value distribution. For instance, we find that there are many similarity values between 0.5–0.6, so we discard these values, which will not be conducive to generating the topic evolution maps.

Fig. 10 hows the global topic evolution trends of mental models at each time span. Each node represents the local topic in a different time period. The color of the node is marked with red, blue, green, which refer to the strong, medium, weak correlation between global topics and local topics. The adjacent nodes are connected by colored flows to indicate the different correlation patterns between local topics in adjacent times. Some weak correlation nodes (green) and flows (green) are omitted to better understand the evolutionary dynamics.

In Fig. 10, we select global topic 1 as an example to further describe the topic dynamic evolution of mental models from the global to local level; the details are as follows. Global topic 1(Fig. 10(a)) mainly focuses on the research of mental models in systems and management, including the knowledge structure constructed of mental models, the risk evaluation of knowledge management, and the R&D and application of mental models in the system.

Local topic 1 in 2001–2005 has a strong correlation (red node) with global topic 1, indicating that the topic has maturely developed at first in this time span. Before this period, the topic was in a developing or readjusting status because there was mainly a weak correlation (green node) between local topics and global topic 1. However, local topic 1 steadily evolves forward to a mature status from 2001–2015, which is confirmed by the strong correlation (red nodes and flows) after that time span. More detailed evolving strategies are as follows: During 1980–1995, global topic 1 was developing or readjusting status, and

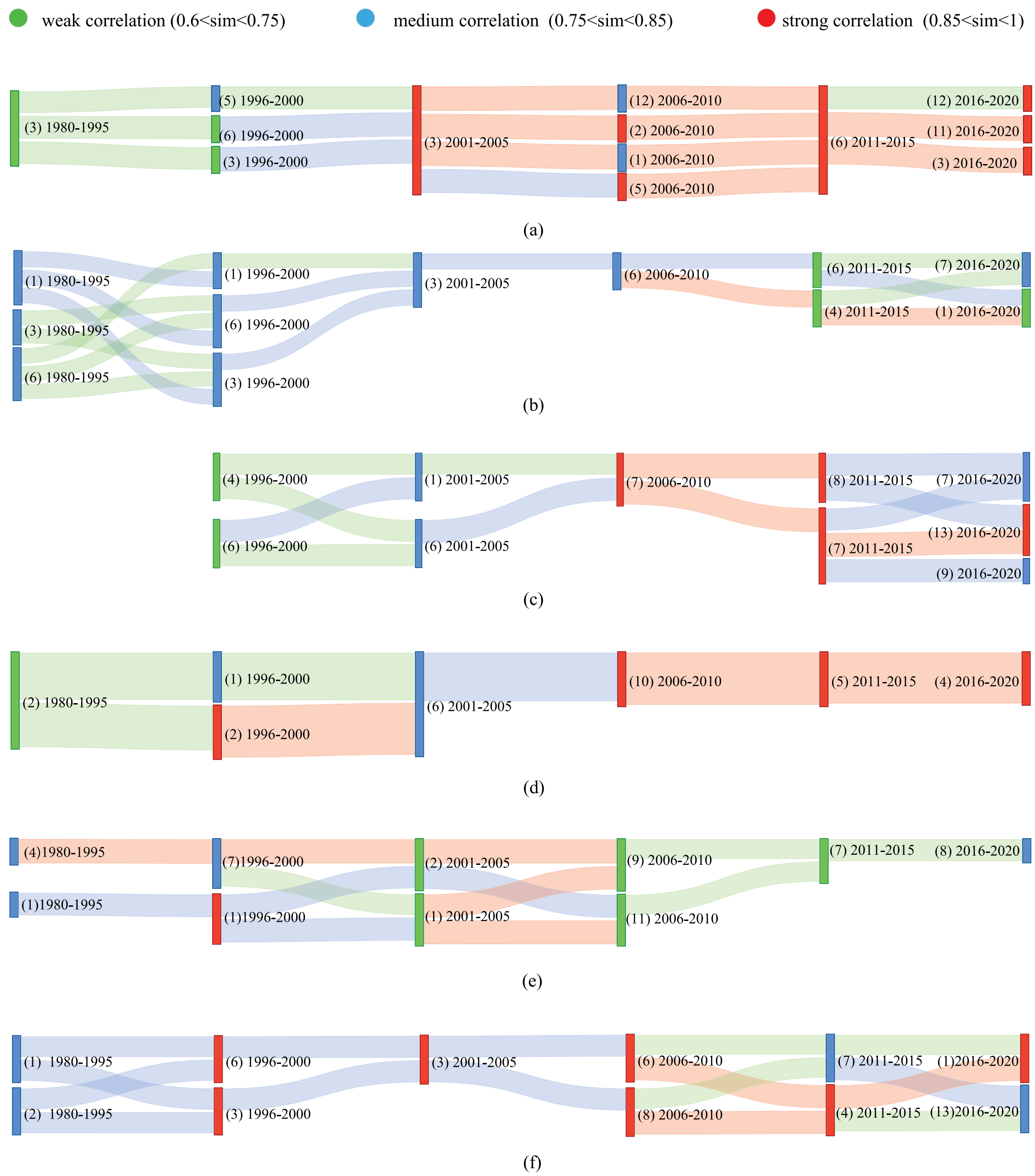


Fig. 10. Topic evolution maps of mental models.

studies on users' cognitive and emotional systems of mental models emerged.

By 1996–2000, it gradually split into research on user cognitive analysis and user information interaction, as well as more attention on user mental in the design system. From 2001–2005, the first moment of maturation for global topic 1, studies on user mental health evolved to the knowledge management of systems and steadily evolved forward. The studies focus more on decision-making and information management within a complex system. However, in the next periods of 2016–2020, global topic 1 is split into several subtopics with different system situations, such as the mental construct constructed in game situations and the member's mental construct of the management system in a corporation.

5.3. Evaluation measures

The evaluation of topic evolution can be roughly divided into two categories: topic content evolution evaluation and topic strength evolution evaluation (Zhou et al., 2016).

Topic content evaluation is usually presented by topic content quality to explain the semantic coherence of words among the topics. Topic strength was also defined as the intensity of the topic evolving over time. To verify the performance of our work, we adopt the three types of topic evolution generation methods mentioned above, namely, DTM, CTH, and PLSA, to compare with our proposed method (denoted as LDA+Word2vec in this section) from the topic content and topic strength perspectives. Topic content evaluation There exist a certain number of methods that can be used to evaluate the topic quality through coherence measures. Topic coherence was used to measure

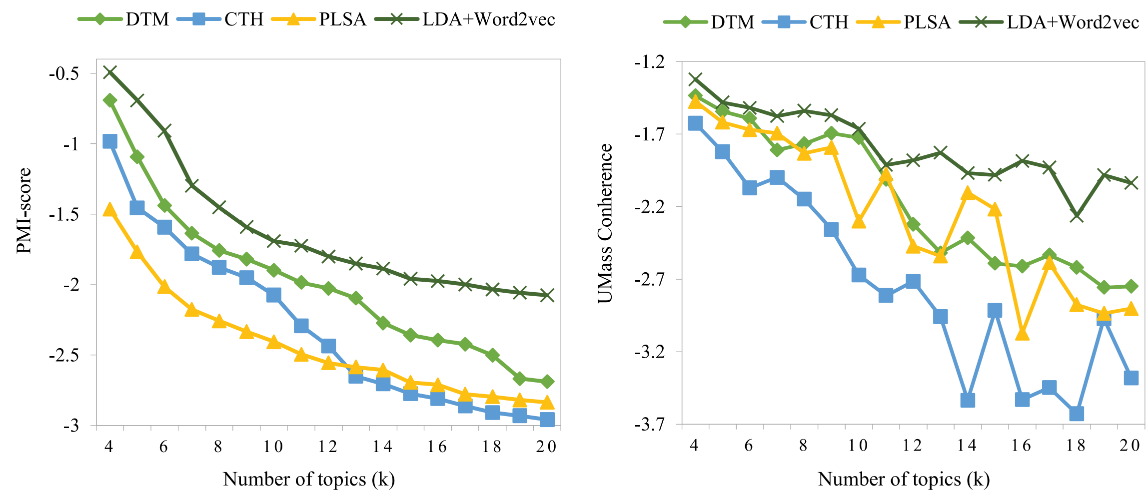


Fig. 11. Topic content evaluation based on PMI-score and UMass.

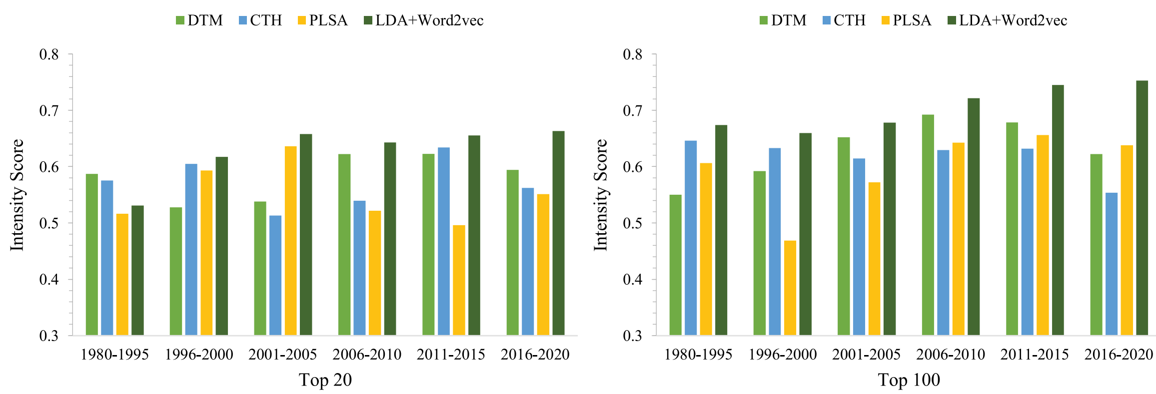


Fig. 12. Intensity score of time slices.

topic content quality by considering the word semantic coherence of topics. The higher the coherence score is, the higher the quality semantic coherence of topic content. In this section, we leverage the pointwise mutual information score (PMI score) (Lin et al., 2014; Newman et al., 2010) and UMass (Mimno et al., 2011) to measure the semantic coherence of topics. These indicators are both standard evaluation metrics in the literature (Yang et al., 2017).

The PMI-score uses the pointwise mutual information (PMI) to measure the semantic coherence of topics. Given a topic k, we obtain the PMI-score by choosing the top-n most likely words w_1, w_2..., w_n.

$$PMI(k) = \frac{2}{n(n-1)} \sum_{1 \le i < j \le n} log \frac{p(w_i, w_j)}{p(w_i)p(w_j)} \tag{4}$$

where $p(w_i, w_j)$ is the joint probability of words w_i and w_j co-occurring in the same document, and $p(w_i)$ is the marginal probability of word w_i appearing in a document. For UMass, the coherence of topic k is calculated as

$$UMass(k) = \frac{2}{n(n-1)} \sum_{i=2}^{N} \sum_{j=1}^{i-1} \frac{p(w_i, w_j)}{p(w_i)} \tag{5}$$

where $p(w_i, w_j)$ and $p(w_i)$ are estimated based on document frequencies (Gao et al., 2019). We calculated these two indicators by increasing the number of words n within global topics. The PMI-score and UMass assess topic quality from word probability and document frequencies, respectively, which can evaluate the topic quality more comprehensively.

Fig. 11 shows the PMI-score and UMass based topic content for each method, DTM, CTH, PLSA and LDA+Word2vec. We set n = 20 in our analysis, and k was varied from 4 to 20. With the k value increased, both the PMI-score and UMass coherence are descended. But the values of PMI-score and UMass coherence show that the proposed method outperforms the others under all conditions. Specifically, as k increases, the score gap between the proposed method and other methods increases.

5.3.1. *Topic strength evolution evaluation*

Regarding strength, we use intensity (Chen et al., 2015). Since the topic evolution is mainly measured by the similarity of the topic words in our work, we treated the average similarity of top-n words in each time slice t as the intensity of topics denoted $Intensity(t, n)$.

$$Intensity(t, n) = \frac{\sum_{k=1}^{K^{(t)}} avgSim_{kn}^{K^{(t)}}}{K^{(t)}} \tag{6}$$

where K is the total topic numbers of time slice t, and $avgSim_{kn}^{K^{(t)}}$ is the averaged similarity of top-n words within the kth topic at time slice t. The higher $Intensity(t, n)$, the stronger the association between words.

Fig. 12 shows the intensity score for every method at different time slices. For the local topics of each time slice, the proposed method achieved the highest intensity score. This means a more accurate ability to obtain similar word information for topics evolving over time. The intensity score is lower than others in the time slice 1980–1995 when the top n=20. This may be due to the low number of documents available during that period. To be specific, when n = 20, the intensity score of the proposed method is slightly higher than others in general. However, after we increased the top-n from 20 to 100, the score gaps

Table A.1
Top words of local topics.

Time span	Local topic	Top words
1980–1995	1	memory- work - task - reason - risk
	2	task - relation - differ - metaphor - attach
	3	cognitive - approach - system - mean - relation
	4	theory - reason - condition - infer - bias
	6	design - spatial - problem - infer - display
1996–2000	1	spatial - descriptive - team - perform - train
	2	team - process - use - effect - perform
	3	process - use - system - inform - user
	4	depress - self - use - attach - student
	5	link - group - social - nurse - judgment
	6	user - experience - base - study - inform
	7	reason - condition - theory - premise - infer
2001–2005	1	problem - child - relate - spatial - reason
	2	reason - experience - condition – theory - infer
	3	system - learn - use - inform - process
	4	use - task - visual - test - result - design
	5	knowledge - mean - management - group
	6	team - student - study - use - effect
2006–2010	1	learn - knowledge - organ - base - organize
	2	risk - inform - use - base - knowledge
	5	system - market - develop - management
	6	user - system - design - visual - group
	7	student - learn - concept - study - teach
	8	user - design - problem - study - gender
	10	team - share - effect - perform - group
	11	child – theory - spatial - reason - text
	12	decision - use - make - study - inform
2011–2015	3	decision - make - cognition - situation
	4	user - design - use - problem - base
	5	team - learn - share - effect - perform
	6	system - use - management - develop - approach
	7	student - care - use - study- science- child
	8	student - study- understand - concept -learn
2016–2020	1	user - system - design - study- interact
	3	learn - study- knowledge - management - research
	4	team - share - perform - care - patient
	7	student - theory - study- reason - represent
	8	use - user - management - decision - design
	9	system - student - think - change - cognit
	11	system - health - use - social - stakeholder
	12	risk - decision - communication - use - change
	13	learn - student - use - educ - develop

between our method and others widened accordingly. These results indicate that the proposed method is more efficient and accurate for massive corpora.

6. Conclusion

In this paper, a novel constructing framework of topic dynamic evolution was proposed, which integrated several strategy applications. First, the use of combining LDA and Word2vec to extract topic vector representations fully considers the contextual information of topics. Many studies that obtain topics are merely based on probability statistics models such as LDA, CTH, and DTM, which fail to capture the entirety of the document because they use a unigram representation that considers a word independently (Yue & Zhai, 2008). This combination method of vectoring and summing the weights of topics generated by LDA modeling accurately expresses the information of the document.

Second, the collected documents are grouped by year and categorized into two categories, Entire and part, to denote the research contents of the overall time and different time spans, respectively. Then, the correlation of inter topics is measured by the cosine similarity between their vector distribution, and three patterns of positive correlation are defined, including strong correlation, medium correlation, and weak correlation. From that, we finally constructed a paradigm of evolution analysis from the macro level to the detail level, which contains the general evolution of global topics of entire documents and the detailed evolution of local topics in different time span documents. These paradigms can help us both understand the information evolution between the overall continuous-time and the different time spans, as well as the developing status of global topics and merging/splitting flows of local topics. The correlation strength between global topics and local topics indicates whether the global topics have been a mature developed status. The merging and splitting flows of local topics indicate knowledge transfer during adjacent time periods.

Then, the proposed method of topic dynamic evolution analyses is applied to explore the evolution trends of the collected mental models related to 3984 documents. Two types of topics are extracted, consisting of six global topics and several local topics in each of the six time spans. The shirking and expanding trends of global topics are detected to present a global perspective of changing trends for mental models, similar to the aforementioned evolution described for global topic 1, and the evolution information can be acquired with combined Fig. 10 and Table A.1.

Finally, after quantitative comparison and objective metrics evaluation, the proposed method outperformed both in topic content evolution and topic strength evolution. Specific performance in the strong topic coherence of global topics and the high word average similarity of local topics. This demonstrated the superiority and usefulness of our proposed approach over the conventional method of topic evolution studies.

In conclusion, this study integrated LDA and Word2vec harmoniously to analyze the topic evolution of the context of a corpus. This combined the advantages of both the probabilistic-based topic models and word embedding representation, avoiding non-contextual responses and sparseness compared to those of conventional topic evolution methods. In addition, by generating global and local topics, topic evolution analysis is conducted from both macro and micro perspectives, respectively, which includes topic distribution under the overall timeline, as well as the information transfer process between adjacent time spans, helping researchers to comprehensively grasp the evolution of relevant research from a multidimensional perspective. With quantitative evaluation, mental models are chosen as an application target and further verify the superiority of our work in the massive corpus.

Despite the many contributions above, there are also some limitations in this work. We applied the proposed framework of topic dynamic evolution in limited-scale documents, which may not detect all detailed information of related domains accurately. In addition, the time span was divided by human judgment, which also needs to explore a scientific solution approach in the future.

There are several directions worth further investigating. The methods of this paper can be applied to analyze the information dynamic changes of other fields, such as news hot spots and rumor spread. Moreover, other information within articles such as nation, co-citations, authors, references, and the words semantic migration in a topic can also be considered in the topic evolution analysis, which is also our next work in the future.

CRediT authorship contribution statement

Jian Ma: Conceptualization, Methodology, Software, Data curation, Writing - original draft. **Lei Wang:** Conceptualization, Writing – review & editing. **Yuan-Rong Zhang:** Writing – review & editing. **Wei Yuan:** Writing – review & editing. **Wei Guo:** Writing – review & editing.

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.

Data availability

The authors do not have permission to share data.

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Appendix

Table A.1 shows the top words of local topics in Fig. 10.

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