

Research on the Evolution Analysis Framework of Keywords for Intelligent Agents Oriented to Monitoring the Frontiers of Disciplines

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Abstract: Promptly identify and study new-generation disciplines to provide support for technological strategy and resource allocation. Research has shown that large language models can be used to study literature on intelligent agents to some extent. The problems of keyword evolution analysis, multi-source data integration and automation have not been solved by the current methods. A framework for the evolution analysis of keywords is put forward in this paper to track the leading edge of disciplines based on the evolution analysis of keywords and the technological progress of intelligent agents. The framework is based on intelligent agents, collects data from multiple sources, and sets up four modules for extraction and standardisation, topic modelling and clustering, evolution identification and signal detection, and thus achieves full-process analysis of the data from collection to result output. A multi-granularity tracking and multi-dimensional feature fusion method are used by the framework to improve the timeliness, accuracy and interpretability of monitoring. Intelligent agents can autonomously complete complex tasks and perform better than a single model; according to CAICT's 2025 industry report, fully packaged general intelligent agents outperform some top-level large models, and the core is to build a closed-loop system via dynamic planning engines and tool calls. Intelligent agents can be introduced to correct the shortcomings of traditional measurement methods in dynamic characterization and intelligence level, and a new type of monitoring for all areas can be provided.

Keywords: Agent, keyword evolution, monitoring of academic frontiers, analytical framework, topic modeling.

1. Introduction

In order to develop the strategic plan for science and technology research and allocate research funds, high-efficiency cutting-edge research directions need to be identified. Frontier technologies refer to the newest and leading directions of innovation activities; they have high innovation levels and excellent development prospects, but are also very uncertain. Continuously observe how the frontier is changing to guide new-technology research and development and scientific innovation.

Scientific and technological literature provides the foundation for the data in frontier identification. Academic papers are the research results that scholars have been studying; patent documents contain technical solutions and industrialisation information, and are often used to evaluate innovation ability; funded projects align with national strategies. Fluctuations in the frequency of keywords, changes in co-occurrence, and shifts in clustering are all indicators of alterations to research focus and trends. Therefore, for a long time, researchers have been observing changes in academic trends by studying the development of keywords.

The current analytical paths have methodological deficiencies [1]. Data cleaning, term standardisation and trend interpretation all require human intervention at this stage, so large-scale monitoring is not feasible. Most of the above methods only identify themes at the annual level and fail to track changes in quarters or even months. In terms of integrating multi-source literature, the existing research has only reached the stage of data source concatenation and lacks in-depth integration at the feature level.

Recently, the development of intelligent agents based on large language models has been progressing rapidly. They can

sense, plan, decide and use tools independently to carry out all kinds of analysis work. The Shanghai Academy of Social Sciences' "Global Information Development Report (2025)" has designated 2025 as the "first year of AI intelligent agents" and indicated that artificial intelligence is now capable of autonomous operation in perception and cognition. Intelligent agents can be used to conduct keyword evolution analysis and meet the demand for high-efficiency, in-depth monitoring of work. This paper aims to build an intelligent agent analysis framework for monitoring disciplinary frontiers, explains the composition logic and operating mechanism of this framework, and provides a reference tool for frontier monitoring.

2. The Intersection of Agent Technology and Frontier Monitoring Needs

Agents are a research focus in the field of artificial intelligence, and they refer to system entities that can perceive their environment, make independent decisions, and carry out actions. The three types are autonomy, reactivity and initiative [2]. Agents have a perception, cognition, decision-making and execution module, and after adding large language models, their natural language understanding and tool invocation capabilities have been significantly improved. The "Fangsheng" benchmark test conducted by the China Academy of Information and Communications Technology (CAICT) shows that general agents outperform some top-level large models in this test; the reason is that they can form a "perception-decision-execution" closed loop via a dynamic planning engine and tool invocation mechanism.

Frontier monitoring of technology methods has several obvious constraints: the research frontier changes rapidly in

the short term, so the monitoring needs to have a high time resolution; analysing the semantic connotations, co-occurrence relationships and evolution trends of key words requires a higher level of semantic understanding; heterogeneous data such as papers, patents and fund projects need to be integrated from multiple sources; and the analysis results should have a traceable logical chain to facilitate understanding of the formation process of the frontier.

The technical features of the agents meet the above requirements. The two links in the link are: data collection and cleaning; topic identification and trend analysis. The previous way was to process them manually, and as the amount of data increased, so did the work. The autonomous decision-making ability of agents can connect these steps into an automated pipeline and reduce human intervention; planning and reasoning capabilities can be used to track the dynamic changes in keyword co-occurrence networks and extract multi-scale evolution paths; and the semantic understanding function of large language models can be employed to evaluate the newness and relevance of research directions at the level of theme connotations, rather than relying solely on character matching.

Existing studies provide support for this way. Bâra and Oprea (2025) have developed a generative multi-agent bibliometric framework that includes customised analysis generation, full-text retrieval and report output modules, and can parse natural language instructions into executable scripts to perform data cleaning, network construction, topic modelling and frontier topic identification, produce reproducible results, and surpass existing tools such as VOSviewer in functional integration [3]. In 2025, IBM Research's work has also supported this view and indicated that agents may be used to actively conduct research on scientific literature.

3. The Theoretical Foundation and Methodological Evolution of Keyword Evolution Analysis

Keyword evolution analysis has developed independently to some extent. To understand why and how agents are used in the course of development, one must first be aware of the problems that have occurred. Keyword evolution analysis in bibliometrics studies how the distribution of terms changes over time to identify shifts in disciplinary focus and the generation logic of the frontier. Keywords are condensed expressions of literature; their frequency fluctuations indicate changes in research interest, co-occurrence relationships show the direction of reorganization of disciplinary knowledge structure, and tracking the temporal sequence of clustering results can also reveal differentiation and intersection of themes.

With the development of these methods, fixed statistics have been replaced by dynamic tracking of keyword analysis, and single-frequency measurement has been converted into multi-dimensional measurement [4]. The first types of methods only used high-frequency word statistics and frequency sorting, ignoring the structural relationships and derivative paths. To solve this problem, co-occurrence analysis was used to construct a domain-knowledge network based on co-occurrence relationships and thus reveal the arrangement of themes in the discipline. CiteSpace is now available in clusters and can identify new words and display time-series plots for citation analysis.

Topic models have been applied to this problem in recent years. LDA is a generative model that can automatically discover the topic structure of large corpora. Dynamic topic models add a time dimension to LDA to show how the strength of topics, terms and their associations change over time. BERTopic and other new models have better coherence and diversity than LDA. Yin (2026) combined time-adaptive dictionary-constrained LDA with bi-calibrated dual-granularity DTM to conduct an evolutionary analysis of AI-related papers published in WOS from 2014 to 2023. Research has shown that generative AI, large language models and multimodal learning have all developed rapidly since 2021, while traditional machine learning has been declining [5].

Some results have been obtained, but the current methods are not ideal. First of all, the process is disjointed; there are separate stages for data cleaning, term standardisation, topic identification and trend analysis, and no unified scheduling or quality control. Secondly, the integration of multi-source data is still at a surface level of concatenation; although papers, patents and projects have explored various aspects to reveal the cutting-edge direction, complementary integration at the feature level has not been effectively achieved. Thirdly, the time granularity is not fine enough; although the annual level is suitable for observing long-term changes, rapid signals at the quarterly or monthly level will be easily smoothed out. Fourthly, the interpretation of the results is still manual; it cannot automatically identify frontier signals and early warning mechanisms. It serves as the foundation for the intervention of intelligent agents.

4. Construction of the Intelligent Agent Keyword Evolution Analysis Framework

Based on the analysis of the characteristics of intelligent agents and the keyword evolution analysis method, this paper builds an intelligent agent keyword evolution analysis framework for monitoring the frontier of disciplines. The framework takes the intelligent agent as the core of execution, organized in a three-layer structure of "data layer-analysis layer-application layer", covering the process from data collection to decision support.

The Data Layer is to collect and pre-process multi-source literature data. The sources of data are academic papers (Web of Science, CNKI), patent documents (Derwent Innovation, USPTO) and fund projects (National Natural Science Foundation of China). The intelligent agent will perform collection, deduplication and filtering based on the predefined discipline domain and search strategy in the collection stage. An intelligent agent conducts text cleaning, word segmentation and keyword normalisation in the pre-processing step. Li Zeyu and others (2025) reported that the accuracy rate of term relationship judgment by AI intelligent agents reached 92.32% [6].

The four modules of the analysis layer are responsible for the main analysis function. The keyword extraction and standardisation module uses the semantic-understanding capability of the intelligent agent to extract keywords from the title, abstract and keyword fields, and performs synonym merging and standardisation. The topic model and clustering module use LDA and BERTopic, etc., to find topic structures and semantic relationships comprehensively. A dual-granularity Design of the evolution trend identification

module tracks changes in topic strength, keyword composition and inter-topic relationships at different time scales using "year + quarter". The frontier signal detection module builds evaluation indicators in four dimensions: novelty, growth, influence and innovation, and automatically screens research directions with frontier potential [7].

The three functions of the application layer are visualisation display, report generation and warning push, selected by the user. The visualisation section shows time-series animations of keyword co-occurrence networks, Sankey diagrams of topic evolution, and emergence word detection maps. The report generation module will automatically generate a standardised monitoring report based on the selected time range, disciplinary domain and analysis depth. The warning push module will notify users of substantial growth or new prominent features in a topic proactively.

The framework operation is a closed-loop structure of "perception-planning-execution-feedback". When the intelligent agent detects the addition of new literature in the data layer, it plans a task sequence according to the predefined goals, sequentially invokes each module in the analysis layer for analysis, and finally outputs the results to the application layer. At the same time, it will adjust the following analysis plan based on the user's feedback and continuously improve the accuracy and timeliness of the monitoring.

5. Empirical Progress and Key Issues in Agent-Based Keyword Evolution Analysis

The above framework is to be verified by experiments. At present, some initial empirical results have been obtained in several fields by studying the evolution of keywords through agents. Although these studies do not directly validate the framework proposed in this paper, they provide indirect support for the feasibility of the agent method in literature analysis and offer references for framework improvement.

Currently, the two types of empirical explorations are available. One is to design a multi-agent collaboration framework, divide the task and cross-validate the results, and thus improve both the coverage and accuracy of frontier topic mining. Another is that the agent is contained in some subroutines, such as keyword extraction, text classification and topic modelling. Tokenisation and term normalisation in the pre-processing stage of data cleaning can be performed by agents to reduce human intervention; topic clustering and trend analysis are also among the areas where agents can provide support. However, the existing work has not explored the application scope and adaptation conditions of agents in detail, and a systematic comparison of performance under different data volumes and literature types is still lacking.

Pavithra and Savitha (2024) have compared the performance of the five methods for handling dynamic text at the topic model level: LDA, HDP, NMF, BERTopic and DTM. The results showed that DTM had the strongest adaptability to the changing times [8]. Another empirical study using BERTopic analyzed 25,907 Web of Science documents, extracted 230 topics, and kept 33 core topics after consistency screening, with all coherence values exceeding 0.8 [9]. Based on the above analysis, while topic models are suitable for large-scale corpus processing, their semantic resolution and temporal granularity are relatively coarse; thus, they cannot directly support the capture of fine-grained frontier signals.

The present empirical studies also have some deficiencies. Different works use different datasets, preprocessing procedures and model parameters, and there is no unified benchmark test and evaluation system to compare the results horizontally. Large language models may introduce factual biases in the conclusion-drawing stage and thus affect the reliability of monitoring results. Multi-agent collaboration is still in the initial stages of exploration, and most existing frameworks are based on a single agent that handles the entire process; thus, the full potential of multiple agents for division of labour and information sharing has not been realised. Most of the previous empirical studies have concentrated on a few technical areas, and the adaptability of the framework in interdisciplinary scenarios has not been fully investigated. The above deficiencies need to be corrected before this method can be scaled up from a pilot project.

6. Key Technologies and Methodological Support of the Framework

Some required technologies are needed to support the normal operation of the framework. These technologies are natural language processing, topic modelling, network analysis and agent architecture; they correspond to data standardisation, topic evolution modelling, frontier signal evaluation and process automation, respectively.

Automatic keyword extraction and standardisation are the first two. The traditional methods are TF-IDF, TextRank and other word-frequency or graph algorithms; they have a poor recognition effect for low-frequency but relevant new words. Large Language Model Agents can extract representative keywords based on context semantics and domain knowledge. When dealing with multi-source data, cross-database term mapping and synonym merging can also be performed to provide a unified term basis for the following co-occurrence analysis.

Dynamic Topic Models are used to track changes dynamically. LDA assumes that topics are stable over time and thus cannot describe the change process [10]. Dynamic topic models have added a time dimension, but still cannot balance macro trends and micro changes at the same time. The two levels of the framework are annual and quarterly; the annual level covers long-term stable core problems, and the quarterly level monitors changes in the short run. BERTopic is a way to use deep semantic representations and dynamic models for extracting the structure and changes over time in professional texts.

Frontier signal recognition is based on the cross-evaluation of multiple-dimensional features. The four indicators in the system are novelty, growth, influence and innovation: Novelty refers to whether a subject has appeared for the first time or increased substantially in the recent literature; Growth reflects how rapidly the number of publications or the frequency of keywords is rising; Influence is the frequency of citations and co-occurrence intensity; Innovation shows whether a subject has introduced new technical paths or methodologies. Entropy-weight method can be used to assign weights to the dimensions objectively and reduce the influence of subjectivity.

Task planning and tool invocation can be used to automate the whole process. Frontier monitoring generally needs several steps, such as cross-data retrieval, text processing, model calculation and visualisation, and the old way is to

switch and coordinate manually. Divide the whole task into several executable sub-tasks and arrange them in a reasonable order for the intelligent agent. It can be used to build models with scikit-learn and gensim, generate interactive plots using pyLDAvis, and construct co-occurrence relationship graphs via network analysis libraries [11]. Organise the process as an intelligent agent to reduce human operation costs and improve the reproducibility of the analysis results.

7. Conclusion

This paper first presents the methodological development of the keyword evolution analysis method, reviews its development process and deficiencies, and then introduces intelligent agent technology into the analysis process to build a three-tier analysis framework for frontier monitoring. Based on the above analysis, the study has drawn the following conclusions regarding the efficiency of the framework: Traditional keyword evolution methods are limited in three ways: the automation level of the process is low, most steps still require manual operation, the time granularity is generally annual, and changes at the quarterly level are easily overlooked; multi-source data integration is still at the level of database concatenation, and effective integration at the feature level has not been achieved. Therefore, the current method is not suitable for handling large-scale and high-frequency frontier monitoring.

A new way has been introduced by intelligent agent technology. The "Fangsheng" test conducted by CAICT shows that a well-packaged general intelligent agent outperforms some top-level large models in terms of performance, and its "perception-decision-execution" closed loop is highly suitable for the multi-step nature of monitoring and analysis. Embed an intelligent agent for keyword evolution analysis to build an unbroken processing chain of data cleaning, topic identification and trend detection. The three-layer framework in this paper uses an intelligent agent as the scheduling core and integrates multi-source collection, dual-granularity modelling, multi-dimensional evaluation, and report generation into a single workflow. Research on micro-luminescent diodes has shown that, to expand the scope of application, several multi-feature fusion methods have been proposed recently.

Several technical supports are required for the operation of the framework: keyword standardisation extraction, multi-granularity topic modelling, multi-dimensional feature fusion evaluation, and the task decomposition and tool scheduling capabilities of intelligent agents. At present, the intelligent agent method still has problems such as a lack of reproducibility, questionable reliability of generated content, and immature multi-agent collaboration mechanisms. Future research will address the above problems directly.

Future work can be carried out in the following directions:

test the applicability of the framework in more disciplines, extend the analysis scenarios from academic literature to industrial patents and project data, optimise the adaptive strategies of intelligent agents in different fields, and build a systematic result verification mechanism. With the continuous development of intelligent agent technology, keyword evolution analysis will be used for frontier monitoring on a regular basis in the future.

References

- [1] Mazov, N. A., Gureev, V. N., & Glinskikh, V. N. (2020). The methodological basis of defining research trends and fronts. *Scientific and Technical Information Processing*, 47(4), 221–231.
- [2] Wang, L., Ma, C., Feng, X., Zhang, Z., Yang, H., Zhang, J., ... & Wen, J. (2024). A survey on large language model based autonomous agents. *Frontiers of Computer Science*, 18(6), 186345.
- [3] Yin, X. (2026). A temporal adaptive dictionary-constrained LDA and Bi-calibrated dual granularity DTM framework for dynamic topic evolution analysis in academic papers. *Scientific Reports*.
- [4] Klarin, A. (2024). How to conduct a bibliometric content analysis: Guidelines and contributions of content co-occurrence or co-word literature reviews. *International Journal of Consumer Studies*, 48(2), e13031.
- [5] Bara, A., & Oprea, S. V. (2025). AI-augmented bibliometric framework: A paradigm shift with agentic AI for dynamic, snippet-based research analysis. *arXiv preprint arXiv:2511.21745*.
- [6] Li, Z. Y., Liu, W., Wu, W. N., & Guo, Y. Q. (2025). Research on synonymous term mining based on AI agents and keyword mapping graph. *Digital Library Forum*, 21(1), 22–32.
- [7] Xu, H., Winnink, J., Yue, Z., Zhang, H., & Pang, H. (2021). Multidimensional scientometric indicators for the detection of emerging research topics. *Technological Forecasting and Social Change*, 163, 120490.
- [8] Pavithra, C. B., & Savitha, J. (2024). Topic modeling for evolving textual data using LDA, HDP, NMF, BERTOPIC, and DTM with a focus on research papers. *Journal of Technology and Informatics (JoTI)*, 5(2), 53–63.
- [9] Lai, K. K., Hsiao, C. W., & Hsu, Y. J. (2025). Strategic management knowledge map via BERTopic (1980–2025): Evolution, integration, and application. *Applied System Innovation*, 8(5), 142.
- [10] Grootendorst, M. (2022). BERTopic: Neural topic modeling with a class-based TF-IDF procedure. *arXiv preprint arXiv:2203.05794*.
- [11] Sievert, C., & Shirley, K. (2014, June). LDAvis: A method for visualizing and interpreting topics. In *Proceedings of the workshop on interactive language learning, visualization, and interfaces* (pp. 63–70).