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Tracing the technological trajectory of coal slurry pipeline transportation technology: An HMM-based topic modeling approach

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Coal slurry pipeline transportation is an important way to realize green coal logistics. However, there are still challenges in understanding the cognitive aspects of coal slurry pipeline transportation technology development trajectory. This study attempts to trace and predict the technology trend from patent texts through the stochastic process analysis of topic evolution. It helps understand the challenges in the development process of coal slurry pipeline transportation technology. And capture trends and development characteristics of the technology to improve research and development (R&D) efficiency and sustainability. As a result, this study extracts potential technology topics from patent text by using the Latent Dirichlet Distribution method. Then, a Word2vec-based topic word vector model is applied to calculate the cosine similarity between topics. And the HMM-based topic evolution trend model is constructed by introducing the Hidden Markov Model (HMM) which can portray a dual stochastic process. Finally, it is used to analyze and predict trends in the technological evolution of this field. It was found that the advancement of technology related to pulping is fundamental to promoting the development of coal slurry pipeline transportation technology, which is also a common research topic. Finally, technologies related to pipeline transportation capacity enhancement and the industrial application of coal slurry will be the focus of future R&D in this field with broad research and application prospects. This study is intended to provide directions for sustainable R&D activities in coal slurry pipeline transportation technology, facilitate interdisciplinary discussions, and provide objective data for future decisions making for scientists and R&D managers in this field.

KEYWORDS

coal slurry, pipeline transportation, trend analysis, patent analysis, topic modeling

1 Introduction

As China's basic energy source, coal causes staggering pollution and waste during transportation (Li et al., 2021). China issued the Energy Technology Revolution Innovation Action Plan (2016–2030) and the 13th 5-year plan for the development of the coal industry, which emphasizes efforts to build an efficient, green, and modern coal industry system. Coal logistics is a key link between coal production and consumption, and its green transformation and development are crucial to building a modern coal industry system (Li et al., 2020). Currently, the research and development (R&D) of closed transportation technology, such as coal slurry pipeline transportation, has become a major research focus of green coal logistics. In recent years, the pipeline transportation technology has been applied widely in engineering fields, such as pipeline long-distance transportation of iron ore concentrate or nickel-cobalt ore, reservoir dredging, etc. With the development of pipeline transportation technology, it has gradually become one of the important ways for the coal logistics industry to achieve green transformation and sustainable development (Prasad et al., 2020; Das et al., 2021). However, countries with coal-dominated energy use have not fully adopted and promoted coal slurry pipeline transportation, much less achieved real commercial application. For example, in China, 80% of coal is transported by train, 13% by ship, and 7% by truck (Oberschelp et al., 2019). Thus, the development of pipeline transportation of coal is still limited.

Technological advancement is an important factor in promoting the diffusion of environmentally friendly technologies (Rao and Kishore, 2010; Tabrizian, 2019; Markard, 2020). Currently, the immaturity of technology is the key factor restricting coal transportation by pipeline projects for large-scale operation and promotion. From a historical development perspective, the trajectory of coal slurry pipeline transportation technology is also full of high uncertainty. In this case, it becomes extremely challenging to identify and analyze the evolution characteristics and the development trends of coal pipeline transportation technology. In other words, the overall development trend of coal slurry pipeline transportation technology is still unclear. This does not help policy-makers introduce targeted policies or develop more competitive R&D strategies to drive technological advancement (Lai et al., 2020; Yuan and Cai, 2021). Therefore, it is necessary to identify and analyze the evolutionary characteristics and the development trends of coal pipeline transportation technology.

However, relatively little attention has been paid to tracking the evolving trends and characteristics of coal slurry pipeline transportation technology based on objective data. Until now, most research concerning coal slurry pipeline transportation technology has focused on modeling (Das et al., 2020; Singh et al., 2020; Yin et al., 2021), method optimization (Singh et al., 2018; Yang et al., 2019; Singh et al., 2022), and literature review (Mishra et al., 2019; Nunes, 2020; Das et al., 2021). And the research methods are usually based on experiments, surveys, case studies or expert reviews. The resulting lack of research concerning technology trend analysis based on scientific systematic analysis is a fact in this field. Tracking the trend of coal slurry pipeline transportation technology could help scientists and R&D managers understand the technology development characteristics in time to improve the sustainability of future R&D activities. Recently, the increasing number of patents has provided an opportunity to investigate technology trends in specific fields. Patents are reliable data for the quantitative analysis of technology trends, which contain complete and valuable information about a specific product or technology (Yoon et al., 2017). Therefore, this study tracks the development trend and characteristics of coal slurry pipeline transportation technology based on the analysis of patent information.

There are various patent analysis methods, such as patent number analysis (Chen and Lin, 2020), technology classification code analysis (Aaldering et al., 2019a), social network analysis (Aaldering et al., 2019b), and patent map analysis (Renaldi et al., 2021). However, these previous studies often ignore the stochastic process characteristic of technological innovation, which may lead to biased analysis results (Pan et al., 2017; Wei et al., 2020). Since this field is characterized by highly uncertain technological developments, it may be more appropriate to trace technology trends from a stochastic process perspective. A Hidden Markov Model (HMM) includes a double stochastic process, which has outstanding advantages in portraying the dynamic stochastic evolution process. Therefore, we adopt an approach that integrates patent semantic analysis with the HMM. It can better portray the stochastic evolution process of technological topics based on patent semantic information, which provides effective data for the quantitative analysis and prediction of technology trends.

Therefore, this study has the following objectives: ① identifying the potential different categories of technological information by extracting technology topics from patent data about coal slurry pipeline transportation technology; ② tracing the development path of coal slurry pipeline transportation technology based on the HMM modeling of the topic evolution stochastic process; and ③ quantitatively predicting the development trend of coal slurry pipeline transportation technology by using the HMM backward algorithm.

This study has two contributions. First, we are the first to explore the development path of coal slurry pipeline transportation technology from the perspective of patent text mining, and we predict possible development trends. Second, semantic mining techniques are applied to the topic stochastic evolution process analysis, which makes us not only rely on the existing term co-occurrence methods for the measurement of the topic evolution stochastic process.

TABLE 1 Comparison of key features of coal transportation ways.

Type	Advantages	Disadvantage
#0000FF	Short and medium distance transportation	Highest operating costs and low labor productivity (relative to pipelines)
Truck	High flexibility	The most serious environmental pollution
#0000FF	High reliability and long transportation distance	High occupancy rate of land resources (25 acres per kilometer of railway)
Rail	Large volume of coal transportation	Serious pollution along the way
	Strong continuity of operation	High coal loss rate (0.8%–1%)
	Low operating costs (relative to pipelines)	Vulnerable to topographic conditions
#0000FF	Low occupancy rate of land resources	Strict concentration requirements (fluidity and stability effects)
Coal slurry Pipeline	Long transportation distance and large coal slurry transportation volume	Strict flow rate requirements (critical flow rate greater than 1.1 m/s)
	Low degree of environmental pollution (closed transportation)	Limited laying slope (up to 16%)
	Low coal loss rate (below 0.1%)	Easily blocked (settlement characteristics)
	Low cost (long distance or relatively short distance)	Waste of water and high-power consumption
	Strong continuous operation characteristics	

The rest of this study is organized as follows: Section 2 provides a literature review of coal slurry pipeline transportation technologies, text mining, and a technology trend analysis. Section 3 describes the research framework and the research process. Section 4 analyzes the technology's stochastic evolutionary trends and the predicted results. Section 5 provides a discussion. Section 6 summarizes this study.

2 Literature review

2.1 Coal slurry pipeline transportation technology

Coal slurry pipeline transportation refers to the process of using high-pressure pumps to continuously transport coal slurry through closed pipes to end-users (Lahiri and Ghanta, 2008). The United States built the first long-distance coal slurry pipeline in 1957 to transport large quantities of coal over long distances (Kania, 1984). Over the years, many countries have been attracted to exploring this technology. We summarized the major advantages and disadvantages of the existing discussed coal slurry pipeline transportation ways in a compact manner, as shown in Table 1. Subsequently, we will briefly summarize the existing research directions and characteristics in the field of coal slurry pipeline transportation.

From Table 1, it is not difficult to find that pipeline transportation technology has a potentially disruptive impact on the future development of the traditional coal logistics system (Zahed et al., 2018). At present, truck and rail transportation are the main ways of coal transportation. The environmental pollution and economic loss caused by the coal dust emission problem during their transportation is huge (Bao et al., 2020). In contrast, the pipeline transportation method is an important way to achieve environmentally friendly, clean, and economical transportation of coal (Jati et al., 2021). Coal slurry pipelines can effectively reduce NOx emissions and energy consumption during the transportation process of coal compared to railroads and highways (Rao et al., 2020). In addition, coal slurry pipeline transportation has the advantage of low maintenance cost, transportation cost and high safety (Kumar et al., 2014). One of the main challenges lies in the high requirement for laying slope of the pipeline since the limitation of the hydraulic properties of slurry. Thus, several scholars have researched specific sub-technologies to tackle such challenges, such as coal slurry rheological properties (Singh et al., 2017), pipeline detection techniques (Zhang et al., 2019), and coal slurry particle composition (Prasad et al., 2020).

Additionally, there are studies on the cost and economic feasibility of constructing a coal slurry pipeline transportation system by reviewing the previous literature. Strogen et al. (2016) discusses the advantages and the disadvantages of pipeline transportation and proposes an evaluation framework for the economic feasibility and the nonmarket benefits of different means of transportation. Jati et al. (2021) analyzed the economic and environmental benefits of using a coal slurry pipeline, aiming to evaluate its feasibility to replace truck transportation of coal. In addition, some scholars provided solutions to specific technical problems in this field by reviewing the literature. Sinha et al. (2017) investigated the best way to reduce the wear rate by reviewing the research on the pipeline wear rate prediction model. Zaman et al. (2020) classified existing research on pipeline leak detection methods and discussed innovations in existing methods. Some scholars also systematically reviewed the development history of long-distance pipeline transportation technology and discussed the future development trend of long-distance pipelines in Australia (Cowper and Thomas, 2009).

Most research methods in this field were experimental, and contained simulation and method optimization, a literature review, etc. Some studies analyzed the progress of sub-technologies, which were only done by literature review or expert judgment (Khan et al., 2019; Das et al., 2021). In particular, a rapidly increasing number of papers and patents on coal slurry pipeline transportation technology have been published in the last few years. It was difficult for academics to accurately analyze potential technology trends from a large number of papers and patents. Thus, this study attempts to explore the development trend of coal slurry pipeline transportation technology based on patent text mining. In the process, a suitable quantitative method was used for the development characteristics of this technology with high uncertainty.

2.2 Patent semantic analysis

Patent documents are an important carrier of technological information and an up-to-date and reliable data resource to study the development trend of specific technology (Yoon and Song, 2014). In fact, the vast amount of patent data makes it difficult to effectively analyze technology trends by relying only on expert knowledge (Park et al., 2016). With the advancement of text mining technology, various patent semantic analysis methods are emerging, such as topic analysis and vector space modeling. Many scholars use patent semantic analysis methods to mine potential technological information, which is widely used for quantitative analysis of technology trends.

Among them, topic analysis is a popular text mining method that identifies hidden topics in documents based on semantic clustering. Latent Dirichlet allocation (LDA) has become a mature topic modeling method that is widely used in text processing, such as in patent text classification (Kim et al., 2019) and topic identification (Chehal et al., 2021), etc. It provides an effective tool for accurately identifying technology trends from a large number of patent documents.

To be clear, LDA is a typical bag of words model that only extracts relationships between words and documents, without considering the relationships between words. However, word context information is often the most important aspect in text semantic mining (Blei et al., 2003; Li et al., 2018). Word2vec provides a modeling method that extracts feature vectors of words from their contexts to express deep semantic information about the words (Mikolov et al., 2013). Word2vec is also an effective tool to obtain semantic similarity (Zhao et al., 2020). Therefore, to better quantitatively analyze technology trends, we combine the LDA and Word2vec to capture technical information about potential topics in patent texts at the semantic level.

2.3 Technological trend analysis

We analyze and forecast the development trends of specific technologies to reveal their development paths (Liu et al., 2020). However, it is difficult to accurately analyze technology trends due to the stochastic nature of the innovation process and the complexity of technology relationships (Frenken, 2006; Pan et al., 2017). Several studies have found that simulation can portray the potential logical relationships among complex systems (Davis et al., 2007). It can be an effective tool for capturing the potential evolutionary relationships between technologies. Some attempts have been made to use simulation methods to capture potential evolutionary relationships among technology topics. Wu et al. (2014) first proposed a topic evolution trend prediction that integrated the LDA and HMM to predict stem cell topic research trends. Later, some studies analyzed and predicted marine diesel engine and 3D printing technology trends by adopting an approach that integrated the LDA and HMM (Wei et al., 2018; Wei et al., 2020). They tended to calculate stochastic evolutionary relationships among topics by the HMM to quantify the development process of technology trends.

HMM is an application of Markov chain, which is an effective method to solve problems such as inferring future states from known states. It has become a simulation method for quantitatively portraying technology trends. Existing studies have provided important insights for us to accurately identify the technology trends of specific technologies. However, we found that the initial parameters of the HMM in these studies were similar results between topics obtained based on term co-occurrence. Compared with citation analysis, the topic co-occurrence results based on term frequency can better reveal the similarity between topics (Feng et al., 2017). However, the term co-occurrence method is still limited in measuring the semantic similarity between topics (Wang et al., 2012). Therefore, it is necessary to explore the HMM-based approach to explore technology trends at the semantic level.

3 Data and methods

3.1 Analysis framework

This study proposes an analysis framework, as shown in Figure 1. The framework consists of four main components: collection and preprocessing of patent data, extraction of technology topics, identification of topic evolution processes, and prediction of topic evolution trends. It explores the technology trends of coal slurry pipeline transportation technology by mining topic information on their patent data. It is of strategic importance for countries to promote clean transportation technologies by tracking their development trends and predicting their future trends.

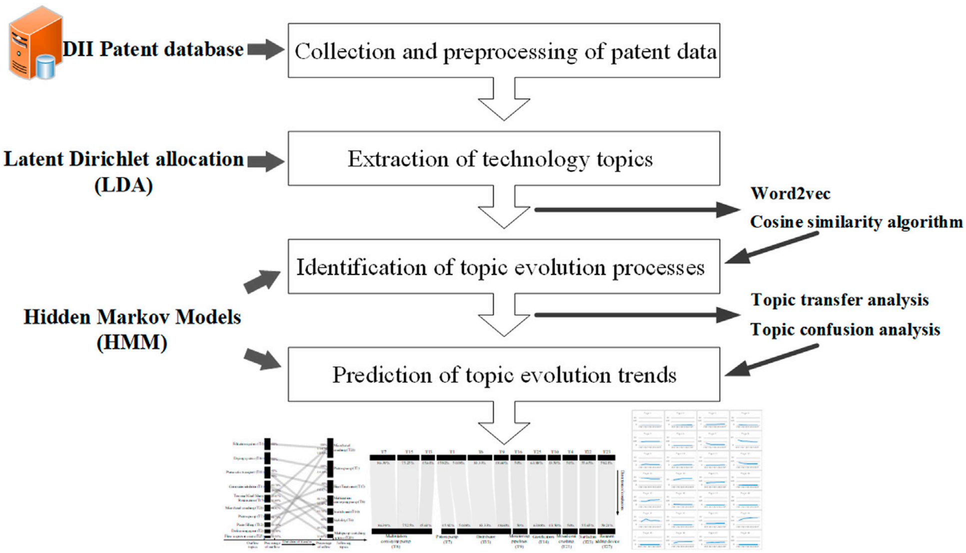

FIGURE 1
Framework for analyzing and forecasting technology trends.

After collecting patent data from Derwent Innovations Index (DII) database and preprocessing them, we first extract technology topics by the LDA. This step involves determining topic numbers to obtain valid topic information. Additionally, we obtain the temporal distribution of topics and classify them. In the subsequent analysis step, an HMM is constructed to portray the dual stochastic evolution process of technology topics, which aim to identify technology evolution trends. To portray the technology topic evolution process from the semantic level, the HMM modeling method based on Word2Vec and cosine similarity is proposed. Then, the technology topic evolution trends are analyzed and predicted by the calculation results of the optimal parameters of this HMM. Finally, based on the above results, we systematically analyze the technology trends of coal slurry pipeline transportation technology.

3.2 Collection and preprocessing of patent data

We use Derwent Innovations Index (DII) database as the patent data source. After repeated screening and testing, this paper uses the term " ((pipeline OR pipe*) AND coal AND (slurry OR slime) AND transport*)" as the retrieval formula to collect patent data. The search was performed in December 2021, and 672 issued patents were retrieved. We further excluded 90 patent records not related to coal slurry pipeline transportation technology.

A patent record consists of many parts, such as a title, abstract, and description. The title and abstract include some key terms that briefly summarize technological innovations. For analysis, we select titles and abstracts from 582 patent records. Then, we remove several meaningless words such as "text", "easy", "user", etc., based on the frequency of each word in the document. In addition, we construct a list of new stop words to remove those words that do not provide useful information for subsequent analysis.

3.3 Extraction of technology topics

This study uses the LDA to extract valid technology topics from acquired patent data. The LDA is a typical bag of words model approach that treats documents as collections of topics and words. This method assumes that each word in the document is drawn from a potential topic. For each document, a topic is drawn from the topic distribution. Then, a word is drawn from the distribution of words corresponding to that topic. Finally, the above process is repeated until all words in the documents are traversed. It generates document-topic distribution and topic-word distribution by sampling regardless of the order that the words appear in. In other words, this process can be understood as extracting multiple sets of words from documents with a certain probability to achieve topic extraction. The number of topics generated by the LDA model needs to be set manually. Here, we can determine the final number of topics based on the perplexity value.

Furthermore, hierarchies can be used for the in-depth analysis of specific technology areas (Li et al., 2019). It can represent the relationship between product components or technical functions in a specific technical field (Choi et al., 2012). Therefore, to analyze the technology trends of coal slurry pipeline transportation technology more systematically and comprehensively, this study is divided into topic categories. We name the topic extraction results and divided the into three categories: "pulping", "pumping " and "end-processing".

3.4 Identification of topic evolution processes

With the rapid development of topic modeling techniques, it is worth considering how to identify technology trends from the extracted results of topics. Actually, the topic evolution process is characterized by double stochasticity, which reflects technology trends. Technical ideas are constantly generating new ideas in the process of updating, and this process is unobservable. This process is observable where these innovative ideas may be documented as patents or literature. Thus, patents can be mined to extract topics to identify technology trends.

Therefore, we construct a discrete HMM to portray the topic evolution process to quantitatively analyze coal slurry pipeline transportation technology trends. The HMM is an observation model with a dual stochastic process, containing a stochastic transfer process of hidden states and a process of hidden states to generate observable sequences. In the HMM, the stochastic transfer process of the hidden states is unobservable, and it can be regarded as a historical change in technology research. The process of generating observable sequences from hidden states can reflect the independent degree of technical research content evolution. The observable states are also patent records. With the HMM modeling of the technology topic evolution process, we can identify technology trends, determine technology directions, and discover technology hotspots and difficulties.

Based on the above idea, we need to clarify the parameters that are used to describe the HMM, which are $\lambda = (Q, V, \pi, A, B)$. Their contents are set as follows.

1) Q is the state set of all possible technology topics. $Q = \{q_1, q_2, \cdots q_N\}$, where N represents the number of technology topics. These states can be transformed with each other, which are unobservable. It is also denoted as the hidden state.
2) V is the set of all possible observable states. $V = \{v_1, v_2, \cdots v_M\}$, where M represents the number of possible observations.
3) π is the probability distribution of the initial state. $\pi_i = P(i_1 = q_i)$, $1 \le i \le N$, where π_i represents the probability of being in state q_i at time $t = 1$. In this study, the similarity matrix between technology topics is used as the initial iteration variable of π_i.
4) A is the transition probability distribution of the hidden state. $A = [a_{ij}]_{N\times M}$, $a_{ij} = P(i_{t+1} = q_j | i_t = q_i)$, $1 \le i, j \le M$. It represents the probability that a topic is transferred from a state q_i to state q_j during the R&D process, where the state sequence I with length T is generated by transferring the hidden state. $I = \{i_1, i_2, \cdots i_T\}$, $i_t \in Q$. i_t is the hidden state at time t.
5) B is the probability distribution of the observable state. $B = [b_j(k)]_{N\times M}$, where $b_j(k) = P(O_t = v_k | i_t = q_j)$, $1 \le k \le M, 1 \le i$. It represents the probability of generating an observable state v_k under hidden state q_j at time t, where O_t represents the observable state variable at time t, which is the observation sequence O. $O = \{o_1, o_2, \cdots o_T\}$ with length T. It represents the annual statistical results of technology topics in this study.

In this study, the topic stochastic evolution process is used to find the optimal parameters A and B for the HMM to achieve $P(O|\lambda)$ maximization. Based on the calculation results of the parameters, thresholds are set to identify the topic evolution process and draw trend graphs, as shown in Figures 2, 3. The *Baum–Welch* algorithm is used in the calculation of the optimal parameters, which is essentially a method for maximum likelihood estimation. In other words, the computational process is a process of stepwise approximation to the lower bound of the maximized likelihood function. However, it only converges to the local extreme points of the log-likelihood function sequence, not the global extreme points. It has been claimed that only suitable initial parameters can obtain local maxima close to the global optimum (Xining et al., 2018). In other words, the setting of the initial parameters is crucial to the calculation results of the optimal parameters of the HMM.

In contrast from previous studies, this study considers optimizing the initial parameters of the HMM from a semantic perspective. Some studies have selected the results of word co-occurrence between topics as the initial parameters to obtain the optimal parameters of the HMM. With the rapid development of text mining technology, it is no longer limited to mining the internal relationship between topics from external features, such as word frequency statistics or word co-occurrence. In contrast, it is of great concern to consider mining key information from lexical contexts to measure inter-topic relationships. Higher similarity between topics implies a stronger possible evolutionary relationship between them. Thus, this study uses the semantic similarity results among topics as initial parameters to calculate the optimal parameters of the HMM.

In this case, this study uses the semantic similarity results between topics as the initial parameters of the HMM. The topic semantic similarity is obtained by using Word2vec and cosine similarity. Word2vec is a vector computation tool that includes the Continuous Bag of Words (CBOW) model and the Skip-gram model. The skip-gram learning model can generate word

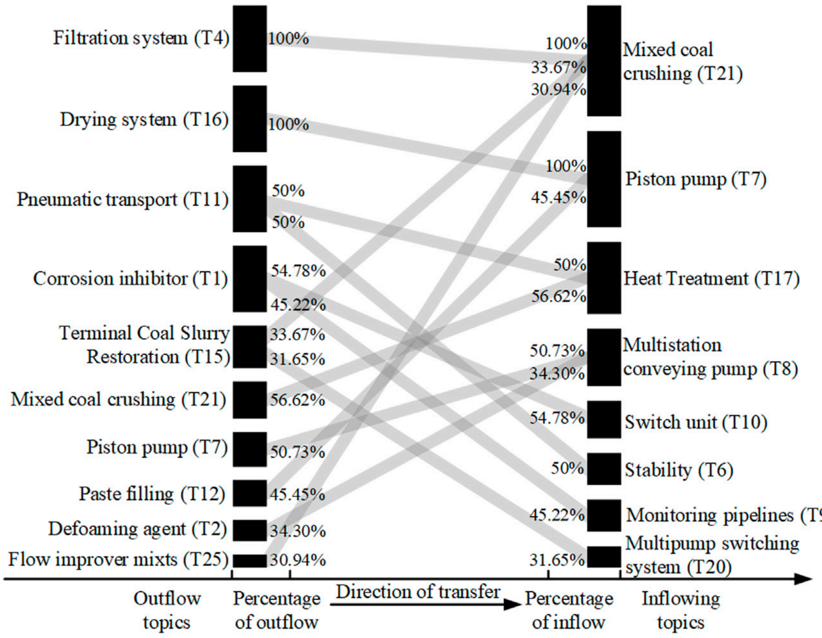

FIGURE 2
The transfer process between technology topics.

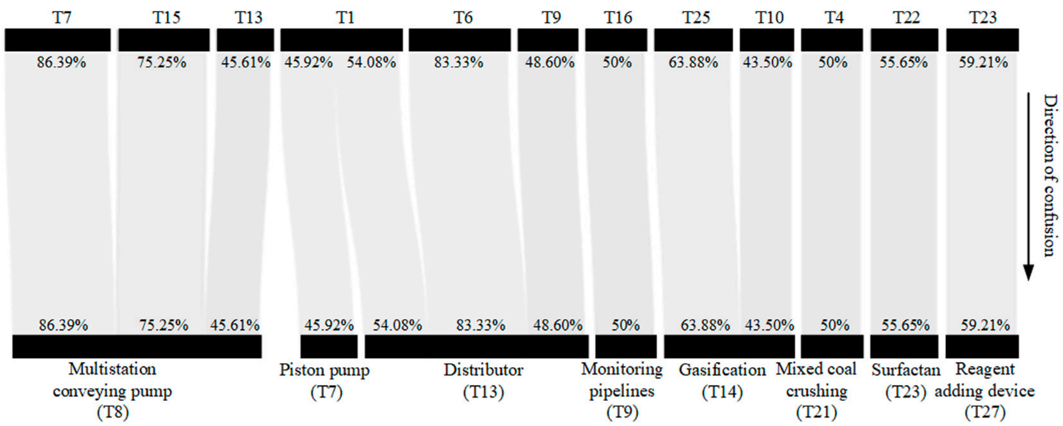

FIGURE 3
The confusion process between technology topics.

vectors from the context of a word. In other words, it can express words as vectors with real values by training the model. These vectors reflect the contextual semantic information of the target words. For this, we use extracted topic terms as objects and apply the skip-gram learning model in Word2vce to obtain the word vectors of these terms. Then, the cosine similarity algorithm is used to calculate semantic similarity between topics. The calculation formula is as follows:

$$\text{similarity} = \cos(\theta)\frac{V_A V_B}{||A| \times |B||} = \frac{\sum_{i=1}^{n} V_{Ai} V_{Bi}}{\sqrt{\sum_{i=1}^{n} (V_{Ai})^2} \times \sqrt{\sum_{i=1}^{n} (V_{Bi})^2}}$$

where V_{Ai} and V_{Bi} represent the components of topic vectors V_{Ai} and V_{Bi}, respectively.

TABLE 2 The results of topic extraction.

Topic	Meaning	Words
1	Corrosion inhibitor	Fluid, equipment, solvent, surface, pipeline, inhibitor, composition, condensate, polymer, aliphatic
2	Defoaming agent	Carbon, catalyst, density, slurry, hydrogen, dry, reduction, pulp, pressure, nitrogen
3	Pulping	Slurry, processing, liquid, pulp, separator, pipeline, settling, pump, transport, connected
4	Filtration system	Water, Vibration, coal, reduce, discharging, slurry, filtering, drying, environment, extracting
5	Dispersant	Acid, salt, slurry, coal, sulphonic, metal, stabilizer, dispersion, copolymer, viscosity
6	Stability	Plate, rod, connected, shaft, fixedly, rotate, support, mounting, coal, block
7	Piston pump	Layer, shell, material, grain, pump, facility, pressure, transportation, motor
8	Multi-station conveying pump	Slurry, coal, pump, connect, pipeline, inlet, pressure, outlet, transmitter, distance
9	Monitoring pipelines	Coal, fluid, portion, pipeline, flow, rate, wall, data, continue, real
10	Switch unit	Valve, control, pressure, drilling, electric, closed, gate, pipeline, station, ball
11	Pneumatic transport	Stir, pneumatic, flotation, tank, spray, pulp, cake, overflow, filter, spray
12	Paste filling	Grout, fill, gangue, coal, underground, slurry, transportation, ground, lift, hydraulic
13	Distributor	Coal, slurry, connected, pipeline, mill, conveying, sieve, screen, pump, tank
14	Gasification	Coal, slurry, tank, powder, mixing, storage, gasification, pipeline, pump, grind
15	Terminal Coal Slurry Restoration	Tank, filter, pump, coal, slurry, concentration, dehydration, sedimentation, thickener, distance
16	Drying system	Chamber, wall, temperature, steam, sludge, centrifugal, treat, wastewater, coal, efficiency
17	Heat Treatment	Boiler, coal, drying, air, tower, heat, furnace, combustion, steam, temperature
18	Cleaning cabin machine	Machine, hopper, cylinder, driving, collecting, cleaning, spiral, power, slime, lifting
19	Concentration and pressure filtration	Waste, transport, filter, coal, thickener, slurry, chute, scraper, clean, grain
20	Multi-pump switching system	Liquid, pump, air, station, pipeline, mechanism, diaphragm, pressure, power, supply
21	Mixed coal crushing	Crusher, Material, ash, cement, mortar, powder, mixing, raw, stirring, construction
22	Annexing agent	Polymer, sulphonated, aliphatic, monomer, vinyl, additive, acid, copolymer, surfactant, lignin
23	Surfactant	Additive, surfactant, oxide, Coal, slurry, powder, water, alcohol, salt, acid
24	Coal particles	Solid, slurry, form, liquid, particulate, coal, mixing, dispersion, compound, produce
25	Flow improver mixts	Tower, layer, stabilizer, sulphonate, bottom, low, tank, concentration, formaldehyde, solid
26	Anti-corrosion coating	Surface, corrosion, polymer, compound, uveous, solution, alkyl, apparatus, mixture, contact
27	Reagent adding device	Coal, slurry, particle, water, pipeline, size, viscosity, conic, coarse, suspension
28	Polymer	Dispersant, monomer, alkyl, water, slurry, ammonium, metal, coal, conic, organic

3.5 Prediction of topic evolution trends

In this study, we predict technology topic evolution trends to identify potential technology growth or decline points. It is important for governments and companies to anticipate potential technological development opportunities and conduct R&D activities strategically. From the above analysis, it was found that the key to achieving the goal is to predict the trend of topic changes over the future years. This belongs to the calculation of the backward probability of the observed sequence in the HMM.

Thus, we first provide the HMM. Then, $\beta_t(i)$ is calculated in the hidden state q_i at time t, which represents the probability that the partial observation sequence from $t+1$ to T is $o_{t+1}, o_{t+2}, \cdots, o_T$. Finally, the observation sequence probability $P(O|\lambda)$ is calculated by continuous recursion, which is calculated as follows:

$$P(O|\lambda) = \sum_{j=1}^{N} a_{ij} b_j(o_{t+1}) \beta_{t+1}(j),\ t = 1, 2, \cdots T-1$$

where, in the step of providing the HMM model λ, the optimal parameters A and B obtained in the previous step are used as the initial values of the HMM input parameters in this study.

Moreover, in a given HMM step, this study uses the optimal parameters A and B obtained in the previous step as the initial values of the HMM input parameters. Additionally, in the input step of the observation sequence O, the proportion of technology topics in the known year t is given. Then, after continuous recursion, the structure of the technology topics in the forecast period is obtained.

4 Results

4.1 Results of technology topic identification

We determine that the number of topics is 28 based on the perplexity score of the LDA model, and the results are shown

TABLE 3 The classification results of topics.

Category	Topic and number
pulping	Defoaming agent (T2), Pulping (T3), Dispersant (T5), Distributor (T13), Cleaning cabin machine (T18), Mixed coal crushing (T21), Annexing agent (T22), Surfactant (T23), Coal particles (T24), Flow improver mixts (T25)
pumping	Corrosion inhibitor (T1), Stability (T6), Piston pump (T7), Multi-station conveying pump (T8), Monitoring pipelines (T9), Switch unit (T10), Pneumatic transport (T11), Multi-pump switching system (T20), Anti-corrosion coating (T26), Polymer (T28)
end-processing	Filtration system (T4), Paste filling (T12), Gasification (T14), Terminal Coal Slurry Restoration (T15), Drying system (T16), Heat Treatment (T17), Concentration and pressure filtration (T19), Reagent adding device (T27)

TABLE 4 The annual distribution results of topics based on categories.

1967–1980			1980–2010			2010–2021		
PUL	PUM	END	PUL	PUM	END	PUL	PUM	END
T13	**T26**	**T4**	T13	T26	**T27**	T13	T7	T16
T23	**T1**	**T16**	T22	**T6**	T4	T23	T20	T12
T18	**T10**		T23	T7	**T12**	T25	T10	T14
T24	**T7**		T18	**T8**	T16	**T3**	T26	**T17**
T22			**T21**	**T20**	**T14**	T2	**T9**	**T15**
			T2	T1		**T5**	T6	
			T25	**T11**			T1	
							T8	
							T11	

Note: PUL, pulping; PUM, pumping; END, end-processing. The topic number in bold font represents the first appearance of the technical topic.

in Table 2. After obtaining the technology topics, we divide the results of the topics into three categories based on the composition of the coal slurry pipeline transportation systems.

The three technology categories are considered as the “pulping”, “pumping” and “end-processing”. The “pulping” category addresses technologies related to the production process of coal-water slurry. The “pumping” category addresses technologies related to the transport of coal slurry along a pipeline to its destination. The “end-processing ” category addresses technologies involved in the reprocessing or utilization of coal slurry after it reaches the end terminal. Identifying technological categories of technology topics is very useful for the systematic analysis of technology trends. Then, we divide all topics into categories with the help of domain experts, and the results are shown in Table 3.

In addition, we also obtain the annual distribution of technology topics based on the results of category classification; the results are shown in Table 4. In Table 4, the topic number in bold font represents the first appearance of the technical topic.

4.2 Analysis of the topic evolution processes

After obtaining the results of technology topics, we obtain the word vectors of all topics by Word2vec. Based on this, the semantic similarity between topics is calculated by using the cosine similarity method, and the results are shown in Table 5. Then, we calculate the optimal parameters A and B, which are the transfer process and the confusion process in the optimal state, and the results are shown in Tables 6, 7. They present the stochastic evolution processes of topics in a quantified way. From Tables 6, 7, it was found that the self-transfer rate of most topics is above 40%, and the self-confusion rate is above 50%. These topics are concentrated in the “pulping” category and the “end-processing” category. Furthermore, we use the calculation results from Tables 6, 7 to set thresholds to present the topic evolution process. We draw the relationship chains with the optimal transfer probability above 0.3 and the optimal confusion probability above 0.4 as trend graphs, and the results are shown in Figures 2, 3.

Figure 2 shows that T1 (corrosion inhibitor) and T11 (pneumatic transport) have the highest outflow rates.

TABLE 5 The semantic similarity results of topics.

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8	. . .	Topic 28
Topic 1	1	0.132	0.077	0.021	0.198	0.059	0.103	0.206	. . .	0.114
Topic 2	0.132	1	0.015	0.006	0.050	0.007	0.019	0.121	. . .	0.033
Topic 3	0.077	0.015	1	0.021	0.011	0.047	0.074	0.180	. . .	0.028
Topic 4	0.021	0.006	0.021	1	0.022	0.005	0.010	0.047	. . .	0.016
Topic 5	0.198	0.050	0.011	0.022	1	0.015	0.027	0.189	. . .	0.186
Topic 6	0.059	0.007	0.047	0.005	0.015	1	0.025	0.125	. . .	0.010
Topic 7	0.103	0.019	0.074	0.010	0.027	0.025	1	0.166	. . .	0.027
Topic 8	0.206	0.121	0.180	0.047	0.189	0.125	0.166	1	. . .	0.159
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	1	. . .
Topic 28	0.114	0.033	0.028	0.016	0.186	0.010	0.027	0.159	. . .	1

TABLE 6 Matrix of optimal transfer relations between topics.

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8	. . .	Topic 28
Topic 1									. . .	
Topic 2		0.657						0.343	. . .	
Topic 3							0.126	0.269	. . .	
Topic 4									. . .	
Topic 5					0.844				. . .	0.363
Topic 6						0.667			. . .	
Topic 7							0.176	0.507	. . .	
Topic 8	0.137							0.188	. . .	
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Topic 28									. . .	0.9

T1 moves to T9 (monitoring pipelines) and T10 (switch unit). T11 is transferred to T6 (stability) and T17 (heat treatment). This reflects the growing maturity of corrosion protection and the dense-phase transport technologies, which are the basis for the research in other technologies. Next, T15 (terminal coal slurry restoration) is transferred to T21 (mixed coal crushing) and T20 (multi-pump switching system). Due to the development of terminal coal slurry reprocessing technology, fine grinding technology and multi-pump switching control technology are gradually becoming common research topics. This trend can also be found in the transfer process from T4 (filtration system), T15 (terminal coal slurry restoration), and T25 (flow improver mixts) to T21 (mixed coal crushing), where T21 has the highest inflow percentage. Additionally, with the development of pipeline transportation technology, T7 (piston pump), T8 (multi-station conveying pump), and T17 (heat treatment) have become targets for technology transfer. This means that many studies are gradually turning to the technical research direction of improving the transportation efficiency of coal slurry.

From Figure 3, T8 (multi-station conveying pump), T13 (distributor), T14 (gasification), and T27 (reagent adding device) are the terminals of multiple confusion relationship chains. This shows that the technical research related to these topics is trending and appealing. Among them, T8 has four chains of confusing relationships from T7 (piston pump), T15 (terminal coal slurry restoration), T13 (distributor), and T19 (concentration and pressure filtration). This means that pump-related technology is a popular research direction, with more technical results. The pump is the core equipment in the transportation process, which is directly related to transportation safety and stability. In addition, there are some topics with few or even no confusion relationship chains, but they have a high rate of self-transfer. This means that the technology R&D associated with them is difficult. However, they attract much attention from academics and practitioners. These include T5 (dispersant) and T24 (coal particles). Coal water slurry is a fluid fuel with coarse particle suspension characteristics. Additives, as an effective method to control the properties of coal slurry, such as concentration, stability, and flowability, are highly researched. However, the molecular structure of additives varies with the quality of different coal types,

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TABLE 7 Matrix of optimal confusion relations between topics.

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8	. . .	Topic 28
Topic 1							0.459		. . .	
Topic 2		0.224							. . .	
Topic 3			1						. . .	
Topic 4				0.5					. . .	
Topic 5					0.668			0.034	. . .	
Topic 6								0.166	. . .	
Topic 7								0.864	. . .	
Topic 8								0.591	. . .	
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Topic 28					0.143		0.082	0.077	. . .	0.118

resulting in limited versatility. Consequently, technical research related to these topics has been difficult.

4.3 Prediction of topic evolution trends

The relationship matrix in the optimal state is calculated in the previous step and it is applied to the topic prediction step. We verify the effect of the prediction model. Using topics from 2010 as the prediction base period, the topic share prediction results in 2011–2015 were obtained by the backward algorithm, and the RMSE was calculated as 0.036. The HMM-based prediction model was determined by experts to have effective prediction performance. Then, we chose the patent data from 2020 as the prediction base period. The predicted percentage results of technology topics generated over 2021–2025 are shown in Figure 4.

In Figure 4, we can see that the trends of some topics trend higher considerably over the prediction period. These topics are T24 (coal particles), T14 (gasification), and T17 (heat treatment). They are related to the industrial application of coal slurries. For example, particle control technology can meet the different requirements of end-users for coal slurry concentration and particle size, which is beneficial to the industrial application of coal slurry. Hence, technical research that facilitates the improvement of industrial applications on coal slurry deserves attention in the future. Additionally, some topics have a slightly increased percentage of growth over the next 5 years. Although the growth is not substantial, it can continue to focus on these technologies. For example, technologies related to T26 (anti-corrosion coating), T15 (terminal coal slurry restoration), and T27 (reagent addition devices). Their research heat is gradually stabilizing and has certain application prospects.

Additionally, T8 (multi-station conveying pump) shows a rapid downward trend over the prediction period, indicating that it will not be a future research focus. Multiple pump operation transport technology has gradually matured in long-distance pipeline transportation. It has the characteristics of a simple structure and easy installation and is already widely used in the mineral industry. Additionally, technology development related to T21 (mixed coal crushing) has moved in other directions as surface coal supply technology has improved. The predicted results show that the development trend of this topic has declined after a short-term rise. The current large-scale production of high-quality coal slurry is no longer a technical challenge. There is also a decreasing trend in T12 (paste filling), T7 (piston pump), and T13 (distributor) over the prediction period. This indicates that the technology development related to it is moving toward specialization and has wide application in other fields. Their research and application in the field of coal slurry pipeline transportation will gradually lose attention.

5 Discussion

We discuss the findings and contributions of this study in more detail below and provide arguments for their practical value.

As the first key finding, the results show that topics in the "pulping" category have a high self-transferability probability. They are the starting of many transfer relationship chains, which can easily be transferred to other categories. This indicates that technologies related to the "pulping" category are the basis for technological development, such as defoamers, flow improvers, and coal blending and crushing. This result responds to Das et al. (2021) call for research on coal pulping technology. The development of pulping technology is the premise of increasing pipeline transport capacity and industrial applications (Hu et al., 2021). With the development of technology, technical research has gradually focused on the direction related to the "pumping". That development trajectory is also reflected in the transfer results of the topics.

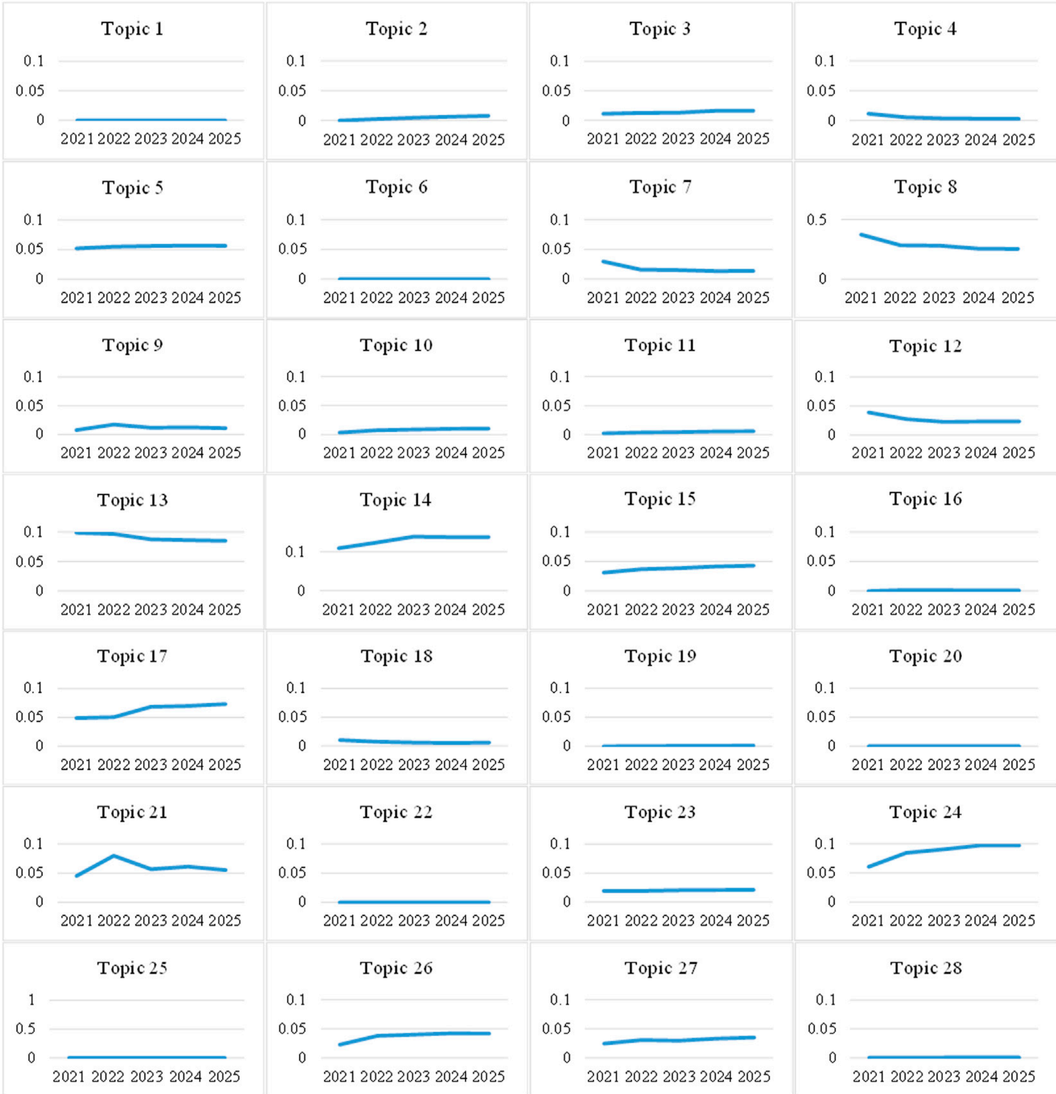

FIGURE 4
The prediction results of the evolutionary trend of technology topics.

Domain experts consider that the transport capacity in coal slurry transport processes has been a long-standing research concern for scholars (Rogovyi et al., 2021). Our data also shows that many topics are diverted to the "pumping" category. Most topics in this category have a low self-transfer probability and are less likely to transfer to other topics, such as plunger pumps, multiple pumping, and stability. It reflects the high degree of independence and stability of technical research in this category.

The second key finding is that the technology hotspots in the field of coal slurry pipeline transportation are concentrated in the "pulping" category. Most topics in this category are confusing targets for other topics, such as separators, coal blending crushing, and surfactants. This indicates that there are numerous theoretical and experimental studies in the "pulping" category, which produce a wealth of patented results (Glushkov et al., 2016). Furthermore, our results show that most technical topics in the "pumping" category have low self-confusion probabilities and are not confusion targets of other topics. This means that the technology in this category is difficult to develop and patent. Interestingly, most of the topics in the "end-processing" category have high self-confusion probability while not being the confusion target of other topics. Topics in this category are mainly related to coal chemical technology. This shows that coal chemical technology has a high technological barrier, although it has high research stability and heat. These findings agree with Xie et al. (2010) who concluded that although coal chemical technology has attracted attention from many countries and scholars, it is very complex and requires multiple inputs with high technical barriers.

The third key finding is that our prediction data shows less potential for technology development in the “pulping” categories, such as mixed coal crushing, separators, and scrubbers. In addition, topics with a rising trend in the future belong to the “pumping” and the “end-processing” categories. This means that technologies in these two categories have promising research and applications. These may also be the frontiers of technologies that need attention, such as technologies related to pipeline corrosion protection and coal gasification. It is worth noting that in our prediction result, only pump-related topics in the “pumping” category have a declining trend in the future and with high rates. This may be due to the limited transport efficiency improvements by the coal slurry quality, the performance of the main pump, and the auxiliary facilities to a large extent (Das et al., 2021). Furthermore, other technologies in the “pumping” category have been developed. Such a trend also confirms the result that many technical topics in the “pumping” category will show an upward trend in the future.

Finally, the innovative HMM-based technology trend research methodology of this study extends the research of Wei et al. (2020). Their research is limited to using co-occurrence features of keywords as a medium to analyze the evolutionary relationships between topics alone, with applications in the fields of 3D printing and marine diesel engines. They emphasize calculating the similarity between topics from the word frequency and the co-occurrence results of topic words. It provides a reference for us to investigate the topic stochastic evolutionary process from the semantic level. Based on the topic results extracted by the LDA, we combine the Word2Vec and the cosine similarity to obtain the semantic similarity results between the topics. The semantic similarity results among the topics are used as the initial variables of the HMM to infer the stochastic evolutionary relationships and the trends among the topics. Therefore, this study can supplement previous studies that analyze technical information from the semantic level of patent texts. Furthermore, in the field of coal slurry pipeline transportation, more insightful information can be identified from patent data *via* text mining and machine learning methods.

6 Conclusion

This study aims to comprehensively understand the development trend of coal slurry pipeline transportation technology through the mining of patent texts. After extracting technology topics from patents, a dual topic stochastic process modeling approach based on semantic similarity is used to quantitatively analyze and predict technology trends. From a methodological perspective, we consider the influence of the term context on measuring thematic similarity. Moreover, this study is also the first to explore the current state of technological development in this field through patent analysis. It helps decision-makers and researchers comprehensively and systematically understand this field to facilitate scientific R&D management and decision-making.

Our results show that the technological evolution of the “pumping” and the “end-processing” category are the main technological development paths with a substantial impact on the coal slurry pipeline transportation industry. In particular, technologies aimed at improving transport efficiency and the coal chemical industry are major areas of technological development. With the maturity of coal slurry preparation technology, the “pumping” and the “end-processing” categories will become popular for research, and the corresponding patent output will also increase. Their development benefits from the technological development of the “pulping” category. However, limited by distance, equipment, end-users, and other objective reasons, the development of coal pipeline transportation technology is relatively slow. It also reflects the difficulty of developing technology in the categories of the “pumping” and the “end-processing”. For example, pumps, valves, and other equipment design and manufacturing requirements are complex and difficult. This may be due to the strong corrosive influence of coal slurry on pipes and various parts. Moreover, the development of coal slurry dewatering technology is not ideal. Currently, even with the dewatered slurry, it still has a higher moisture content than raw coal. It has serious influences on the subsequent use of coal slurry. There are many other technical difficulties such as this. Thus, scholars and researchers need to focus on technological innovation in these two areas.

Despite the contributions, there are still some limitations in this study. First, this study is only based on the analysis of patent texts to trace the development of coal slurry pipeline transportation technology. But not all technical information exists only in patents. Future studies can extend the data analysis to literature and commercial reports to better analyze the comprehensive technical landscape of pipeline coal transport systems. In addition, future studies can also include the application cases of pipeline transportation technology in other fields in the analysis, such as iron concentrate slurry transportation pipeline, phosphorus concentrate slurry transportation pipeline or nickel-cobalt slurry transportation pipeline, etc. Mutual learning from technology experience can promote the sustainable development of coal pipeline transportation technology. Finally, this study only considers the use of first order HMM to build a technology theme trend analysis model. However, the current state of technology is indirectly related to the past state. Then, the higher order HMM can be adopted for future studies to analyze and predict the evolution of technology trends more accurately.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

Conceptualization, JW and KL; methodology, KL; software, KL; validation, JW and LF; formal analysis, LF; investigation LF; data curation, LF; writing-original draft preparation, KL; writing-review and editing, KL; supervision, LF; funding acquisition, JW.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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