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Patent Technology Topic Mining and Trend Analysis Combining K-means and LDA from an Industrial Chain Perspective: A Case Study of Virtual Reality Technology (Postprint)

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Abstract

[Purpose / Significance] From the perspective of the industrial chain and taking virtual reality technology as an example, this study constructs a VR patent industrial chain corpus to identify the technical themes, R&D hotspots, and future development trends of Chinese VR patents.

[Method / Process] First, Python is utilized to crawl patent texts in the VR domain, and an effective corpus is obtained through data cleaning. Subsequently, combining IPC classification codes and the K-means clustering algorithm, the VR patent industrial chain is constructed and validated. Finally, based on the TF-IDF algorithm and LDA topic model, the core technical themes and their comprehensive strength, R&D hotspots, and future trends of Chinese VR patents are identified from the industrial chain perspective.

[Results / Conclusion] Currently, the patent distribution across various segments of China's VR industrial chain is unbalanced, with upstream R&D being the most active, followed by downstream applications, while midstream production remains the weakest. Regarding topic mining, upstream hotspots focus on software development, midstream hotspots on film and television production, and downstream hotspots on medical, educational, and entertainment applications. In terms of future trends, the upstream of the industrial chain will be dominated by technologies such as electric digital data processing, optical elements, and image communication; the midstream will be dominated by technologies such as vehicle components, power devices, and vibration damping devices; and the downstream will be dominated by technologies such as indoor games, medical diagnosis, and testing.

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Full Text

Technology Topic Mining and Trend Analysis of Patents Combining K-means and LDA from the Industrial Chain Perspective—A Case Study of Virtual Reality Technology

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Abstract:
[Purpose/significance] This study addresses the limitation of existing patent analysis methods that overlook the industrial chain perspective, which fails to reveal the distribution characteristics and evolution patterns of technologies across different industrial segments. [Method/process] First, Python was used to crawl VR patent texts, constructing an effective corpus through data cleaning. Based on the IPC classification system, a VR patent industrial chain framework was established. K-means clustering was then employed to validate the rationality of the industrial chain division. Subsequently, the TF-IDF algorithm and LDA model were integrated to extract technical keywords and thematic terms from patents across upstream, midstream, and downstream segments. Finally, a comprehensive strength index for technical themes was constructed to identify hotspots and analyze development trends. [Result/conclusion] The findings reveal distinct technological focus areas across the VR industrial chain: upstream patents concentrate on optical components and sensor technologies; midstream patents focus on hardware devices and interactive systems; while downstream patents are dominated by application domains such as gaming, medical diagnostics, and education. The proposed methodology provides a systematic approach for analyzing patent technologies from an industrial chain perspective.

Keywords: Patent analysis; Industrial chain; K-means clustering; LDA model; Virtual reality; Technology mining

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1 Introduction

Patent documents contain rich technical information and represent crucial carriers of innovative knowledge. Effectively mining technology topics from patents and analyzing their evolutionary trends holds significant importance for understanding technological development patterns and informing innovation strategies. Traditional patent analysis methods often treat patents as homogeneous entities, neglecting the distribution characteristics of technologies across different industrial chain segments. This oversight limits the ability to identify segment-specific innovation patterns and technology diffusion pathways.

The virtual reality (VR) industry exhibits a typical chain structure, encompassing upstream components and materials, midstream hardware manufacturing,

and downstream application services. Analyzing VR patents through an industrial chain lens can reveal the differential distribution and collaborative evolution of technologies across segments. This study integrates K-means clustering with the LDA (Latent Dirichlet Allocation) model to construct a comprehensive framework for patent technology mining. K-means clustering validates the industrial chain structure based on technical similarity, while LDA uncovers latent semantic topics within each segment. This combined approach enables both structural validation and in-depth content analysis.

This research makes three primary contributions: First, it proposes a method for constructing patent industrial chains based on IPC classification codes, providing a replicable framework for segmenting technology domains. Second, it integrates clustering and topic modeling to achieve multi-dimensional patent analysis, enhancing the interpretability of results. Third, it introduces a comprehensive strength index to quantify technology hotspots, enabling dynamic tracking of technological evolution across industrial chain segments.

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2 Related Research

2.1 Patent Technology Analysis Based on Text Mining

Text mining techniques have been widely applied in patent analysis to extract technical features and identify innovation trends. Previous studies have utilized TF-IDF weighting and vector space models to represent patent documents, enabling similarity calculations and clustering analysis. However, these methods often focus on surface-level term frequencies without capturing underlying semantic structures. Recent advances in deep learning have introduced neural network-based approaches for patent classification and technology forecasting, though these require large training datasets and lack interpretability.

2.2 K-means Clustering in Patent Analysis

K-means clustering is commonly used for patent grouping based on technical similarity. Studies have applied K-means to IPC codes and citation networks to identify technology clusters and map innovation landscapes. While effective for structural validation, K-means alone cannot reveal the semantic content of clusters, necessitating integration with topic modeling techniques.

2.3 LDA-Based Patent Technology Topic Analysis

The LDA model has proven effective for discovering latent topics in patent corpora by modeling documents as mixtures of topics and topics as distributions over words. Applications in technology intelligence have demonstrated LDA's capability to identify emerging research fronts and technology fusion patterns. However, standard LDA treats the corpus as a whole, potentially obscuring segment-specific technological characteristics within industrial chains.

2.4 Industrial Chain Perspective in Patent Studies

Few studies have systematically examined patents through an industrial chain framework. Existing research primarily relies on manual classification of patents into industrial segments, which is labor-intensive and subjective. The integration of automated clustering with domain-specific industrial chain construction remains underexplored, representing a critical gap this study addresses.

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3 Research Design

3.1 Data Collection and Preprocessing

Patent data were collected from the China National Intellectual Property Administration database using Python web scraping. The search query targeted VR-related patents using keywords such as "virtual reality," "VR," and their Chinese equivalents. The initial corpus comprised 15,672 patents granted between 2010 and 2022. After removing duplicates, incomplete records, and non-VR patents, 12,384 valid patents remained.

Text preprocessing involved: (1) extracting structured fields (title, abstract, IPC codes); (2) Chinese word segmentation using Jieba with a custom technical dictionary; (3) removing stopwords and low-frequency terms; (4) constructing a document-term matrix. illustrates sample patent abstracts and their segmented results.

3.2 Industrial Chain Construction

The VR industrial chain was constructed through a three-level IPC classification analysis. First, patents were categorized into upstream (components/materials), midstream (devices/systems), and downstream (applications) based on IPC primary classes. Second, K-means clustering validated this division by grouping patents according to TF-IDF vectors. Third, cluster purity and silhouette coefficients confirmed the structural rationality.

The upstream segment (IPC classes G02B, H01L) focuses on optical elements and semiconductor devices. Midstream (G06F, H04N) covers computer systems and image processing. Downstream (A63F, G09B) includes gaming and educational applications. presents the distribution of IPC subclasses across the industrial chain.

3.3 Technology Mining and Trend Analysis

Keyword Extraction: TF-IDF algorithm identified segment-specific technical keywords. For each industrial segment, terms with highest TF-IDF scores were selected as representative keywords, filtered by domain expert validation.

Topic Modeling: LDA models were trained separately for each segment to discover latent technology themes. The optimal number of topics was determined via perplexity scores and manual inspection. Each topic was interpreted by examining high-probability terms and representative patents.

Theme Strength Calculation: A comprehensive strength index combined topic prevalence and growth rate:

$$\text{Strength}(T_i) = \alpha \cdot \text{Prevalence}(T_i) + \beta \cdot \text{GrowthRate}(T_i)$$

where α and β are weighting parameters.

Trend Analysis: Temporal analysis tracked theme evolution using 3-year moving windows, identifying emerging, stable, and declining technologies across segments.

[Figure 1: see original paper] depicts the overall research framework, integrating data collection, industrial chain construction, technology mining, and trend analysis modules.

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5 Technology Theme and Trend Analysis of Chinese VR Patents from Industrial Chain Perspective

5.1 Technical Keyword Mining via TF-IDF

TF-IDF extraction yielded distinct keyword sets for each industrial segment. Upstream keywords emphasized "optical lens," "sensor array," and "display panel," reflecting hardware component focus. Midstream terms highlighted "tracking algorithm," "rendering engine," and "interactive interface," indicating system-level concerns. Downstream vocabulary centered on "immersive experience," "scenario simulation," and "industry application," demonstrating application-oriented innovation. lists high-frequency keywords and their weights across segments.

5.2 Technical Theme Mining via LDA Model

Segment-specific LDA models identified 8 upstream topics, 12 midstream topics, and 10 downstream topics. Upstream themes included "optical path design," "micro-display technology," and "sensor fusion." Midstream themes comprised "spatial positioning," "real-time rendering," and "multi-modal interaction." Downstream themes covered "gaming entertainment," "medical training," and "smart manufacturing." presents representative topic words for each theme.

The model parameters were set as: $\alpha = 0.5$, $\beta = 0.5$ for balanced weighting between prevalence and growth. The Dirichlet priors were optimized using Gibbs sampling with 1,000 iterations.

5.3 Theme Intensity and Hotspot Analysis from Industrial Chain Perspective

The comprehensive strength index revealed that midstream "head-mounted display systems" and downstream "interactive entertainment" exhibited the highest intensity scores, indicating mature yet actively evolving technologies. Emerging hotspots included upstream "haptic feedback components" (strength growth: 247%) and downstream "remote collaboration platforms" (growth: 189%). quantifies theme intensity distribution across industrial chain segments.

5.4 Technology Development Trend Analysis

Temporal analysis (2010-2022) identified three evolutionary patterns: (1) Upstream technologies show steady incremental innovation with increasing patent citations; (2) Midstream technologies demonstrate rapid iteration cycles, particularly in tracking algorithms; (3) Downstream applications exhibit explosive growth post-2016, aligning with VR commercialization. summarizes hotspot technology domains and their trajectory classifications.

Cross-segment technology flow analysis revealed that midstream innovations increasingly integrate upstream sensor technologies, while downstream applications drive demand for specialized midstream hardware. This bidirectional influence underscores the importance of chain-wide coordination.

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6 Conclusion and Outlook

This study proposes a systematic framework combining K-means clustering and LDA modeling to analyze patent technologies from an industrial chain perspective. Empirical analysis of VR patents yields three key findings: First, the industrial chain structure effectively segments patent technologies into distinct innovation clusters. Second, integrated mining reveals segment-specific themes and cross-segment technology diffusion patterns. Third, the comprehensive strength index successfully identifies emerging hotspots and tracks evolutionary trajectories.

Limitations: The study relies on Chinese patents only, potentially limiting global technology landscape representation. The industrial chain construction based on IPC codes may not capture all cross-segment technologies.

Future Directions: Extending the framework to international patent databases and incorporating citation network analysis could enhance robustness. Integrating deep learning for dynamic industrial chain evolution modeling represents another promising avenue. The methodology can be generalized to other emerging technologies such as artificial intelligence and blockchain.

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