Education Insights

Article

Innovation and Practical Exploration of the Education Path of Industry-Education Integration in the Automotive Industry Chain Based on Natural Language Processing Technology

Na Tang [1] and Ling Lu [1,*]

[1] Department of Business, Geely University of China, Chengdu, China
* Correspondence: Ling Lu, Department of Business, Geely University of China, Chengdu, China

Abstract: As the automotive industry chain accelerates its transformation towards intelligence, electrification, and networking, the importance of industry-education integration in talent training and technological innovation has become increasingly prominent. However, the existing industry-education integration model still has problems such as imperfect cooperation mechanisms and disconnection between educational content and industry needs. This study uses natural language processing (NLP) technology as the core tool to deeply mine text data (policy formulation, market analysis, technology research and development, production and manufacturing, sales and service) of the automotive industry chain through sentiment analysis and topic modeling to reveal industry sentiment trends and hot topics. The study found that negative emotions accounted for the highest proportion in policy texts (342 articles), focusing on regulatory constraints and new energy promotion; market analysis and technology research and development were dominated by positive emotions (1742 and 2178 articles, respectively), reflecting the industry's support for innovation and development; negative emotions were prominent in the sales and service field (784 articles), reflecting the concentration of user pain points. Based on the empirical results, this paper proposes an optimization plan for the industry-education integration education path from six dimensions: policy response, technology research and development, intelligent manufacturing, market services, interdisciplinary training, and dynamic adjustment, aiming to promote the precise connection between educational content and industry needs and provide theoretical and practical support for the cultivation of compound talents in the automotive industry chain.

Keywords: industry-education integration; automotive industry chain; natural language processing (NLP); sentiment analysis; topic modeling; talent cultivation; intelligent manufacturing; educational innovation

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1. Introduction

The current development of the automotive industry chain is influenced by new technologies such as intelligence, electrification, and networking. The importance of talent training and technological innovation in the automotive industry chain is becoming increasingly prominent. As an effective talent training model, the integration of industry and education in the automotive industry chain is particularly important in promoting the deep integration of education and the automotive industry and improving the quality of talent training [1]. Although industry-education integration has been widely implemented in the automotive industry chain, there may still be problems such as imperfect cooperation mechanisms and insufficient integration depth [2]. How to improve the cooperation mechanism and strengthen deep collaboration to promote the sustainable development of industry-education integration in the automotive industry chain is the key.

The purpose of this study is to explore a new model of industry-education integration education path in the automotive industry chain inspired by natural language processing (NLP) technology, and to provide support for talent training and technological innovation in the automotive industry chain. The key to the study is how to use NLP technology to optimize the industry-education integration model, thereby enhancing both the quality of talent training and the technological innovation capabilities within the automotive industry chain. This study intends to use literature review and empirical research methods to deeply explore the application of NLP technology in industry-education integration within the automotive industry chain, and to make innovative designs for industry-education integration education paths in the automotive industry chain. The overall structure of this paper mainly includes introduction, related research, research design, empirical analysis, research discussion, etc.

On the theoretical level, this study deepens the concept of industry-education integration education. By introducing NLP technology, this study provides a new perspective and theoretical support for research on industry-education integration. At the same time, it promotes the application research of NLP technology in the field of education and provides research ideas for interdisciplinary research. In terms of practical application, this study processes text data related to the automotive industry chain through sentiment analysis and topic modeling, providing a strong basis for the update and optimization of educational content, which helps schools adjust teaching plans and curriculum settings according to industry needs and cultivate high-quality talents that are closer to market needs.

2. Related Research

2.1. Current Status of Industry-Education Integration around the Automotive Industry Chain

With the rapid development of the automotive industry, industry-education integration around the automotive industry chain has been widely discussed. For example, in the development of intelligent connected vehicle technology, it should be closely integrated with industry trends to promote the coordinated development of talent training and technological innovation through industry-education integration [3]. Bertram et al. believe that training new engineering talents should focus on the actual needs of the modern automotive industry by promoting disciplines aligned with industry development. At the same time, to cultivate future-oriented automotive engineers, it is necessary to build a platform for innovation and practical training based on competency development. This platform should not only focus on the construction of a progressive engineering education practice system, but also be committed to building a dual-teacher engineering education faculty system to ensure that students develop comprehensively under the dual guidance of theory and practice [4]. It can be seen that the industry-education integration model introduces actual industry needs into the teaching process by strengthening the connection between schools and enterprises, thereby improving the pertinence and practicality of education.

However, Zhang and others pointed out that there are a series of problems in the training of new energy vehicle technology professionals under the current background of industry-education integration, such as the curriculum system is out of touch with reality, the professional teaching staff is relatively backward, and the school-enterprise cooperation form is single [5]. At the same time, there may be shortcomings between enterprise mentors and school teachers, and there may be a disconnect between enterprise development and talent training [6]. Since most of the problems stem from the mismatch between the needs of the automotive industry and the school curriculum system, this study argues that educational content must be closely aligned with the real conditions of the industry. Before formally carrying out curriculum formulation, it is particularly important to clarify the needs of the automotive industry chain.

2.2. Application of NLP Technology in the Automotive Industry and Education Field

At present, in the field of natural language recognition, the main research areas of NLP in Chinese include lexical analysis, dependency syntax analysis, word vector representation, word meaning similarity, short text similarity, opinion extraction and sentiment analysis [7]. This method is feasible in the research of automobile industry. For example, Garg pointed out that this technology can be used to analyze the three functions of product evaluation, product image, and reasons for purchase and abandonment in the automobile industry, and truly feedback users' rational rating, emotional evaluation, satisfaction points, and complaints about products, locate the image of the car model in the minds of users, and restore the reasons for purchase and abandonment in the purchase decision-making scenario [8]. Uygun et al. believe that automobile companies can improve how they process unstructured data. The use of BERT model and machine learning methods in NLP can efficiently mine the value of data and continuously improve product experience [9].

In recent years, the application of NLP technology in the field of education has become more and more extensive. For example, NLP technology plays an important role in intelligent question-answering systems, machine translation, sentiment analysis, and topic modeling. Raza et al. used the learning data information of teachers and students in the forum to explore the specific application methods of data mining in mathematics learning forums, focusing on establishing LDA model and cluster analysis for text data, sorting out high-frequency words that appear in the teaching process, and helping educators to deal with educational problems in a targeted manner [10]. Jang et al. used Chinese university MOOC courses as the research object, obtained course review data, used the LDA topic model to extract topics, obtained course evaluation indicators, used the entropy weight method to determine the indicator weights, constructed a course evaluation indicator system, and took a course as an example for empirical analysis [11]. In addition, Putri also used the NLP model to make personalized recommendations for network resources based on students' interests and learning needs to achieve precise education resource supply. Through experiments and data analysis, the results showed that artificial intelligence technology has a significant effect in college network education, improving students' academic performance, learning interest, and motivation [12]. It can be seen that in the field of data mining and analysis in the field of education, NLP technology can analyze a large amount of text data to discover valuable information and trends, and provide support for educational decision-making.

In this study, NLP technology is primarily used to extract relevant information about the automotive industry in order to explore its current state and needs, thereby informing the design of industry-education integration courses.

3. Research Design

3.1. Research Objects

This paper takes the text data of the automotive industry chain in the past five years as the research object, aiming to reveal the emotional trends and hot topics in the industry, and then provide strong support for the integration of industry and education in the automotive industry chain. Among them, the automotive industry chain involves a total of five links, including policy formulation, market analysis, technology research and development, production and manufacturing, and sales and service. The data forms include but are not limited to policy documents, market reports, industry news, etc.

3.2. Data Description

The data sources and acquisition methods are shown in Table 1.

Table 1. Data Sources and Acquisition Methods.

Data item	Data source	Acquisition method
Policy formulation text data	Automotive Industry Network	Web crawler
Market analysis text data	Caijing.com, Autosome	
Technology research and development text data	CNKI, Automotive Industry Network	
Manufacturing text data	Automobile Manufacturing Network, Autosome	
Sales service text data	Boss Direct Hiring, 58.com, Liepin	

3.3. Research Design

3.3.1. Data Preprocessing

In order to improve the effect of natural language processing, this paper performs a series of preprocessing on each text data item. First, special characters are removed, case normalization is performed, stop words are removed, and word form restoration is performed. Then, this paper calls the "Natural Language Toolkit" library in Python and uses the "Word Tokenize" function to segment the RT text data into words or shorter phrases for word segmentation. Subsequently, this paper calls the machine learning classification model "Scikit-learn" library through Python and uses the "Tiff Vectorizer" tool to convert the preprocessed text data into TF-IDF (Term Frequency-Inverse Document Frequency) feature vectors. TF-IDF measures the importance of a word in a document by calculating its term frequency and inverse document frequency across all documents, laying the foundation for subsequent analysis [13].

3.3.2. Experimental Design

In the sentiment analysis part, logistic regression is first used as the classification algorithm. The TF-IDF vector extracted in the previous step is used as the input feature to train the logistic regression model to distinguish the positive, neutral and negative sentiments in each data item. In the model training, 80% of the training set data is used to train the logistic regression model, and 20% of the test set data is used to evaluate the model performance. The sentiment classification results reflect the performance of the model on the test set. The model verification part uses indicators such as Accuracy, Recall, and F1-Score to evaluate the model's performance.

In the topic modeling part, first, the K-means algorithm is used to perform cluster analysis on the data of each text data item, which can be used to discover the number of clusters of similar content. Then, the LDA model is used for topic modeling. This paper extracts a total of 5 topics, and improves the interpretability of the topics by adjusting hyperparameters and performing repeated training (Figure 1).

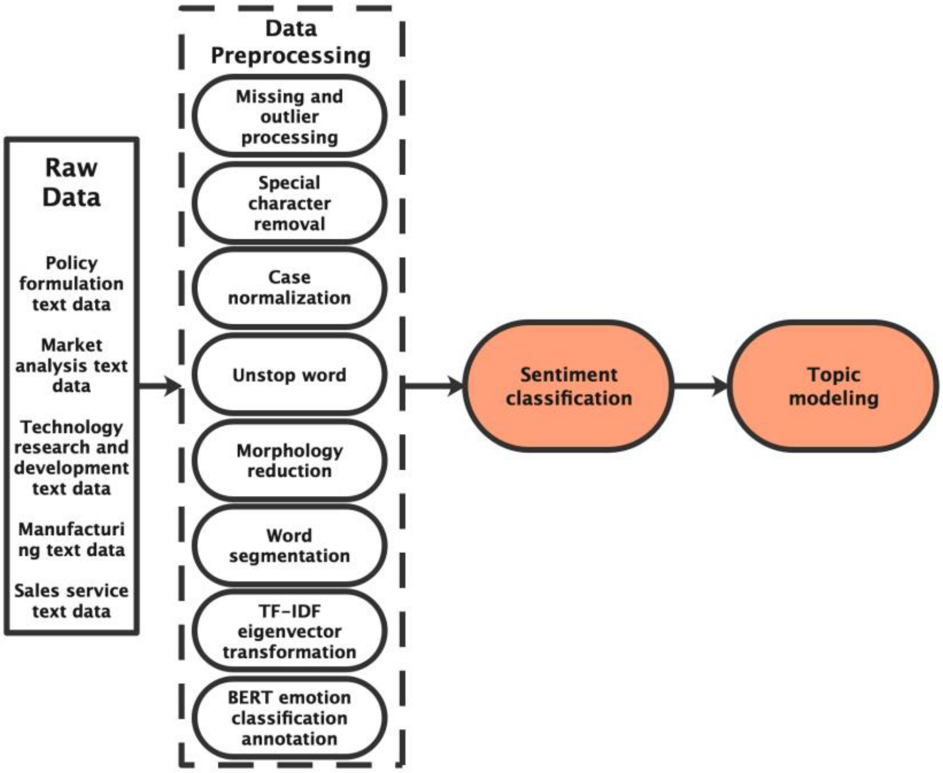

Figure 1. Research Technology Roadmap.

4. Empirical Analysis

4.1. Policy Making

As can be seen from Figure 2, the sentiment analysis results of the automotive industry policy making text data show obvious distribution characteristics. Among them, the number of texts in the negative sentiment category is the largest, reaching 342; the number of texts in the positive sentiment category is second, at 234; and the number of texts in the neutral sentiment category is the least, at only 32. This shows that in the policy making of the automotive industry, the expression of negative emotions occupies a large proportion.

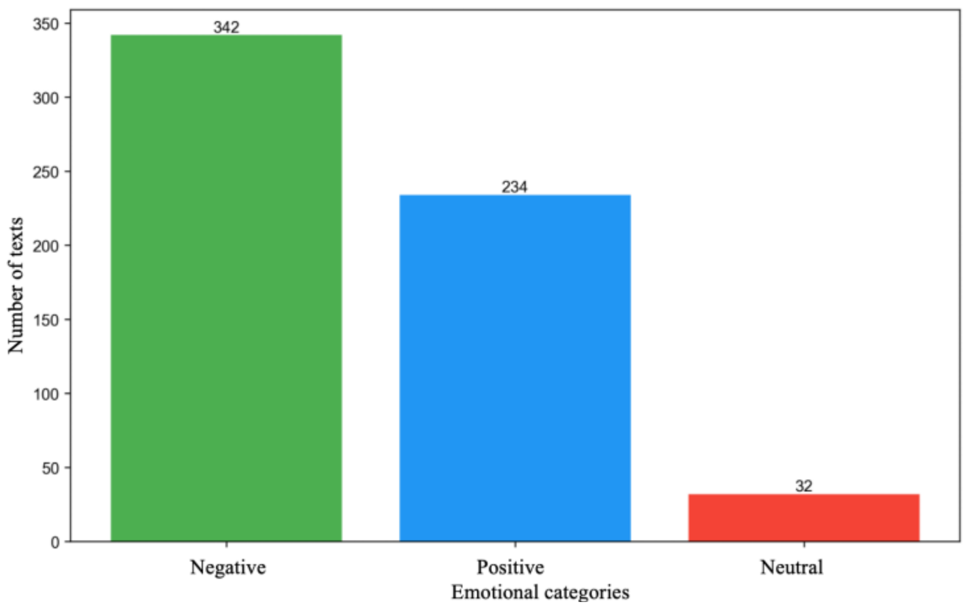

Figure 2. Policy Making Sentiment Distribution Results.

The high proportion of negative sentiment categories in the policy text data of the automobile industry may be due to the following reasons. On the one hand, as a key sector of the national economy, the development of the automobile industry is affected by many factors, such as environmental protection requirements and energy crisis. While promoting the development of the industry, policymakers need to solve a series of urgent problems, such as reducing automobile exhaust emissions and promoting new energy vehicles. This makes the relevant policy texts tend to emphasize norms and constraints, thus carrying a negative emotional tone. On the other hand, the formulation of policies often needs to take into account the sustainable development of the industry and the public interest of society. Some such as raising production standards and restricting the production or sales of certain vehicle types, which will also cause the policy texts to be negative in emotional expression. This also indirectly indicates that the development of new energy vehicles is under close attention and scrutiny. The number of policy texts in the positive sentiment category is also considerable, which reflects the support and guidance of policymakers for the development of the automobile industry. With the advancement of science and technology and changes in market demand, the automobile industry is facing new development opportunities such as intelligence and networking. The government encourages enterprises to increase R&D investment and promote technological innovation and industrial upgrading through the formulation of relevant policies. These policy texts will naturally have positive emotional colors, aiming to stimulate the innovative vitality of enterprises and promote the healthy development of the entire industry. The number of policy texts in the neutral sentiment category is relatively small, mainly because such policies involve more routine affairs, such as market supervision, enterprise registration, product certification, etc. These policies are mainly formulated to maintain the normal order of the market and the stable development of the industry. Their content is relatively neutral and does not carry obvious emotional tendencies, so they account for a low proportion of the overall policy text data.

According to the results of the topic modeling analysis in Figure 3, the text data of automobile industry policy formulation can be divided into five main themes, each with a unique keyword distribution. The text data of automobile industry policy formulation covers multiple aspects, reflecting the diversity and multi-faceted nature of policy formulation. Themes 1 and 4 both involve policy issuance and implementation. Specifically, Theme 1 focuses more on the announcement and dissemination of policy documents, while Theme 4 emphasizes guidance on industrial development strategies, showing the government's active role in promoting the development of the industry. These policies may include support measures for automobile companies, directional guidance for industrial development, etc., aiming to promote the healthy and sustainable development of the automobile industry. Themes 2 and 3 focus on the promotion and application of new energy vehicles, as well as related projects and demonstration projects, reflecting the current focus of automobile industry policies. With the improvement of environmental protection requirements and the intensification of the energy crisis, new energy vehicles have become a core area of policy attention. Policymakers encourage enterprises to increase investment in the research and development and production of new energy vehicles by issuing relevant notices, catalogues and engineering demonstrations, and boost the adoption of new energy vehicles in order to achieve energy conservation and emission reduction goals. Theme 5 focuses on policies in the field of industry and information technology, involving product management and announcements, as well as related affairs of enterprises, reflecting the close connection between the automotive industry and the development of industry and information technology. Against the background of rapid development of informatization, the intelligence and networking of the automotive industry have become a development trend. These policies aim to regulate industry development and improve product quality and safety. At the same time, they support the transformation and upgrading of automobile enterprises to better adapt to market and technological changes.

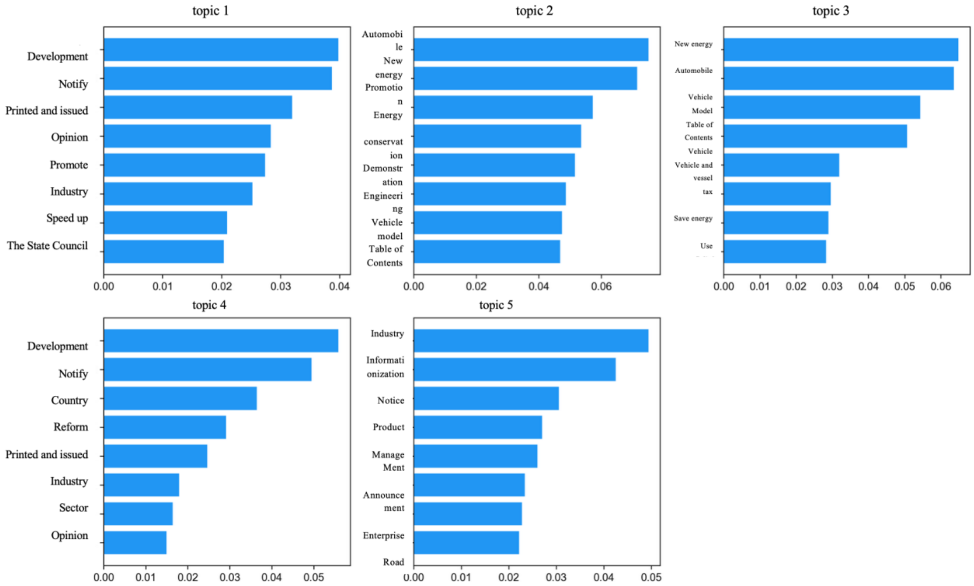

Figure 3. Topic Classification Modeling Results.

4.2. Market Analysis

According to the sentiment analysis results in Figure 4, the number of texts with positive sentiment is the largest, reaching 1742, which is dominant; the number of texts with negative sentiment is 727, which is the second largest; the number of texts with neutral sentiment is the smallest, which is 532. This shows that overall, texts with positive sentiment occupy a large proportion in the data set. The largest number of positive sentiment texts may mean that the market analysis texts in the data set are generally more positively oriented, emphasizing positive content such as development and innovation. The number of negative sentiment texts is second, reflecting that there are also challenges or problems in the market development process. There are relatively few neutral sentiment texts, indicating that most texts have obvious sentiment tendencies.

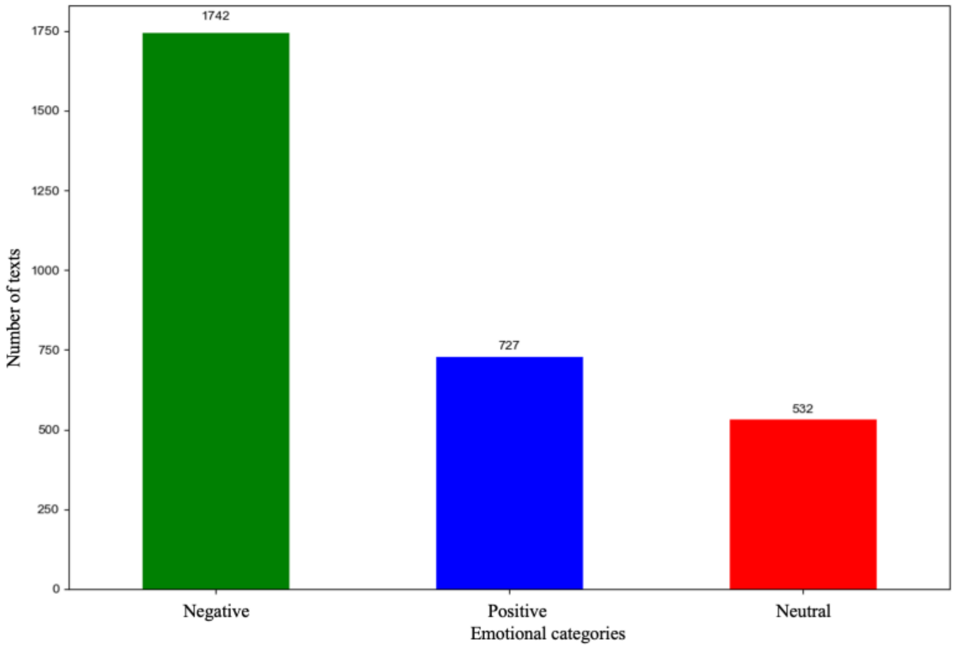

Figure 4. Market Analysis Sentiment Distribution Results.

From the distribution of topic keywords in Figure 5, the text content in the data set is mainly concentrated in several core areas such as automobiles, markets, and new energy. Under different topics, the combination of these keywords is slightly different, reflecting the diversity of policy texts in different focuses. Topic 1 focuses more on enterprises and growth, Topic 2 tends to be development and analysis, Topic 3 emphasizes the Chinese market and future development trends, Topic 4 focuses on electric vehicles and new energy, and Topic 5 involves research, strategy, and brand.

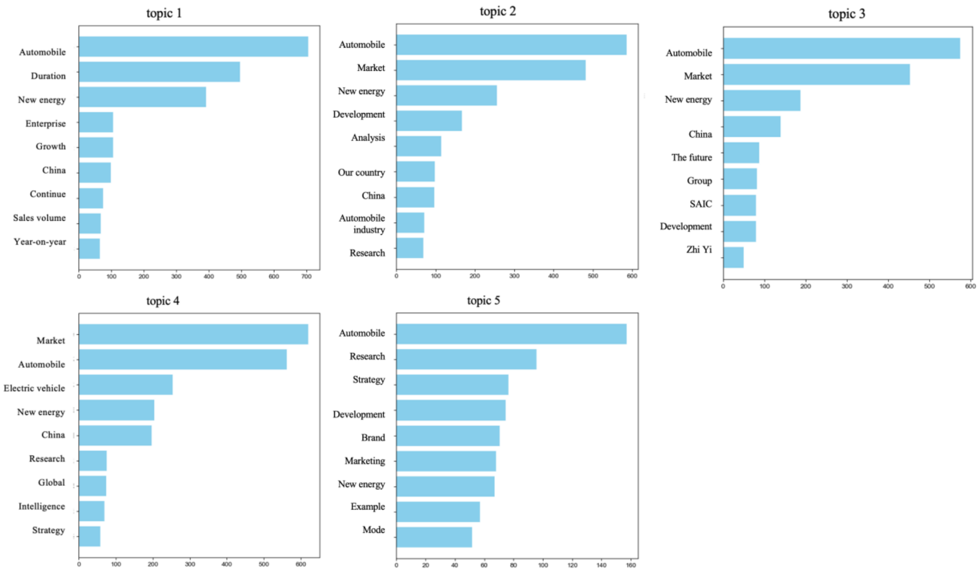

Figure 5. Topic Classification Modeling Results.

4.3. Technology R&D

According to the sentiment analysis results in Figure 6, the number of texts with positive sentiment is the largest, reaching 2178, which is dominant; the number of texts with negative sentiment is 931, which is the second largest; the number of texts with neutral sentiment is the smallest, which is 303. The dominance of positive sentiment suggests that texts related to technology R&D generally emphasize development and institutional support. The largest number of positive sentiment texts may mean that emphasizing aspects such as technological breakthroughs, funding support, and innovation policies. The number of negative sentiment texts is second, which may reflect that there are also some challenges or problems in the technology R&D process. There are relatively few neutral sentiment texts, indicating that most texts have obvious sentiment tendencies.

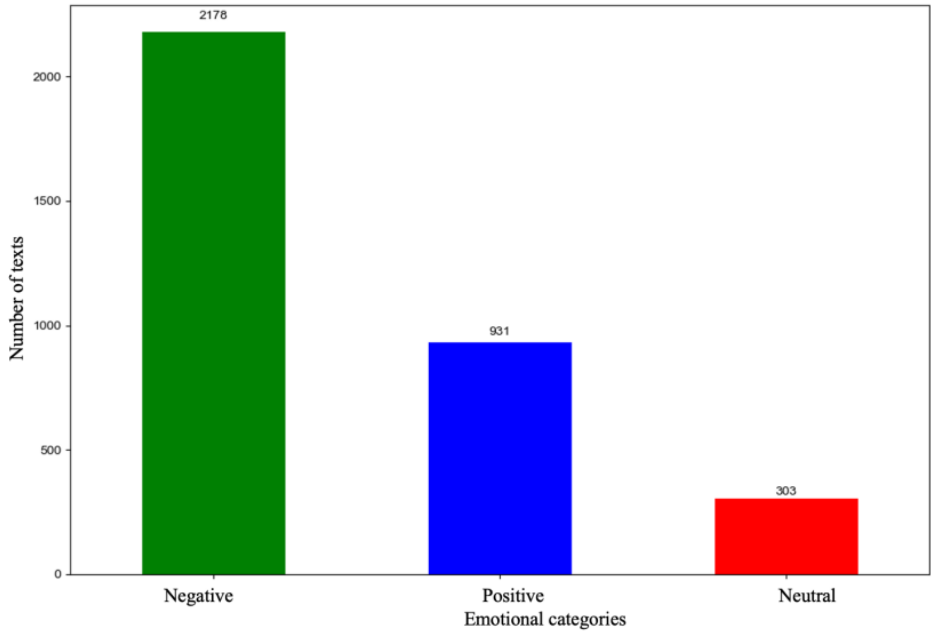

Figure 6. Market Analysis Sentiment Distribution Results.

From the distribution of topic keywords in Figure 7, the text content in the dataset is mainly concentrated in multiple core areas of technology R&D. Under different topics, the combination of these keywords is slightly different, reflecting the diversity of technology R&D texts in different focuses. Topic 1 focuses more on the automotive industry and innovation, Topic 2 focuses on technological research and talent cultivation, Topic 3 emphasizes technology and practice, Topic 4 focuses on electric vehicles and applications, and Topic 5 involves aspects such as intelligence and automation.

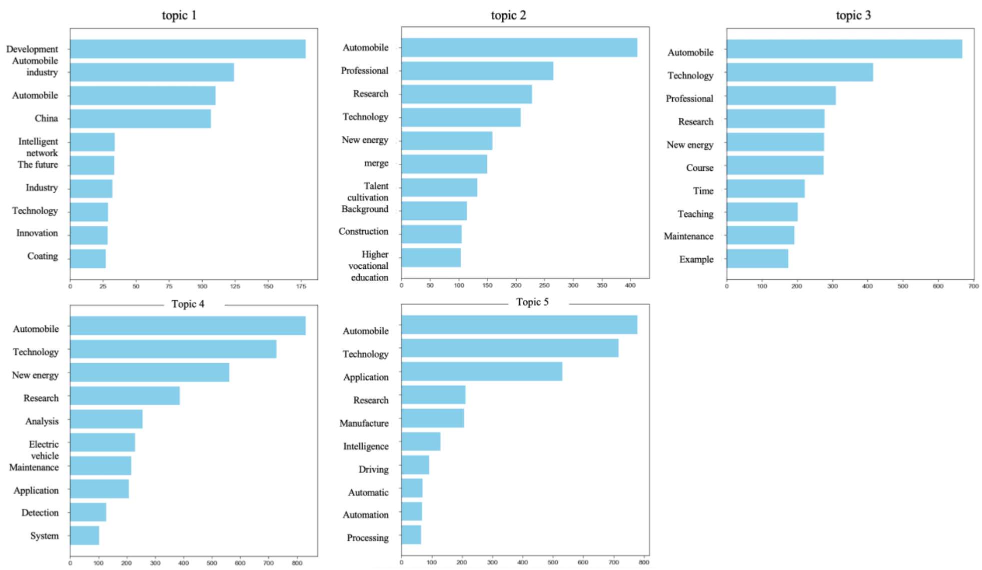

Figure 7. Topic Classification Modeling Results.

4.4. Manufacturing

According to the sentiment analysis results in Figure 8, the number of texts with positive sentiment is the largest, reaching 919, which is dominant; the number of texts with negative sentiment is 479, which is the second largest; the number of texts with neutral sentiment is the smallest, which is 196. This shows that overall, texts with positive sentiment occupy a large proportion in the dataset. The largest number of positive sentiment texts may mean that highlighting themes such as production innovation, automation progress, and industry upgrades. The number of negative sentiment texts is second, which may reflect that there are also some challenges or problems in the manufacturing process. There are relatively few neutral sentiment texts, indicating that most texts have obvious sentiment tendencies.

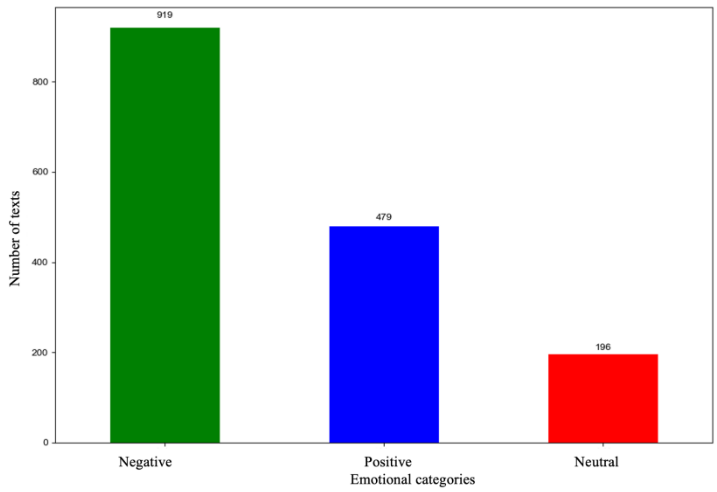

Figure 8. Production and Manufacturing Sentiment Distribution Results.

From the distribution of topic keywords in Figure 9, the text content in the dataset is mainly concentrated in multiple core areas of manufacturing. Under different topics, the combination of these keywords is slightly different, reflecting the diverse emphases within manufacturing-related texts. For example, Topic 1 focuses more on macro-level development and research, Topic 2 tends to be manufacturing and automation technology, Topic 3 emphasizes production management and quality, Topic 4 focuses on industry reports and applications, and Topic 5 involves technical processing and testing.

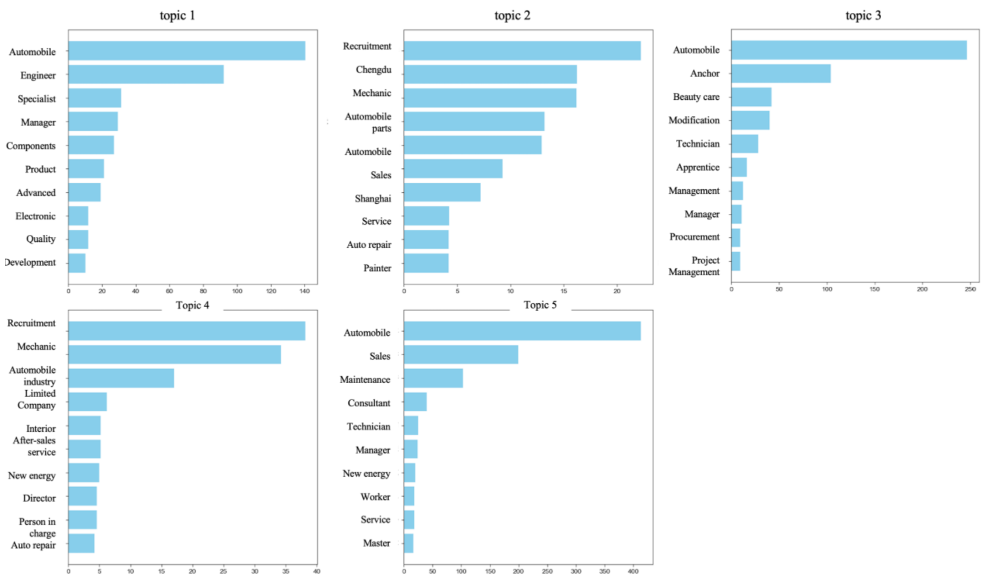

Figure 9. Topic Classification Modeling Results.

4.5. Sales Service

According to the sentiment analysis results in Figure 10, the number of texts with negative sentiment is the largest, reaching 784, which is dominant; the number of texts with positive sentiment is 73, which is the second largest; the number of texts with neutral sentiment is the smallest, which is 63. This shows that overall, texts with negative sentiment account for a large proportion in the dataset. Generally, contain more complaints, customer dissatisfaction, or reflections of service-related issues. This suggests that success stories or customer praise are relatively limited in the dataset. The smallest number of neutral sentiment texts indicates that most texts have obvious sentiment tendencies.

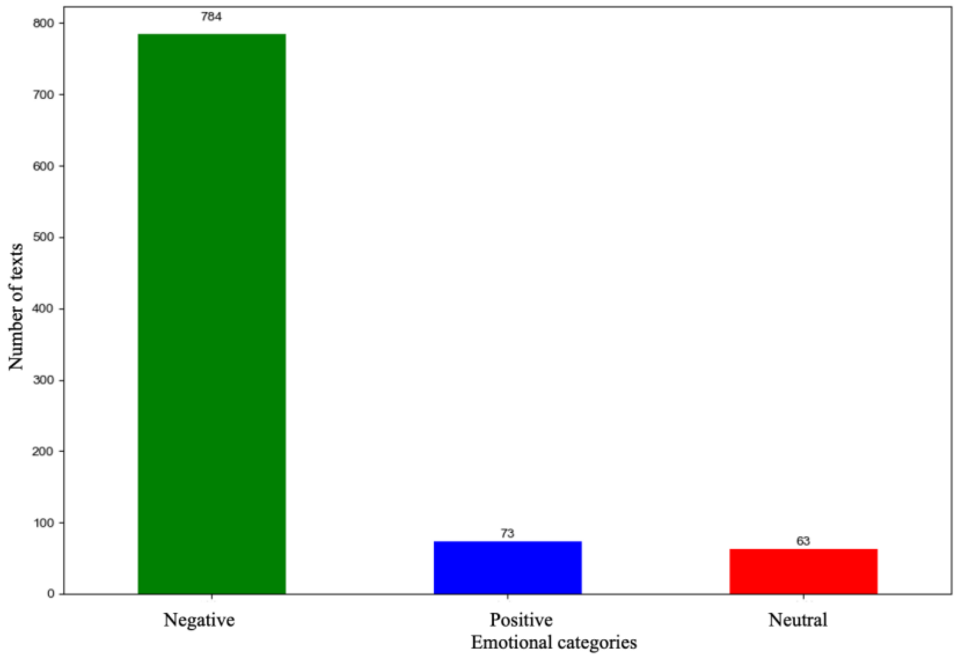

Figure 10. Sales Services Sentiment Distribution Results.

Figure 11 reveals that the sales service texts primarily focus on several key areas. The variation in keyword combinations across topics highlights the thematic diversity within sales service content. For example, Topic 1 focuses more on technology and product quality, Topic 2 emphasizes car detailing and maintenance services, and Topic 3 involves sales and after-sales services.

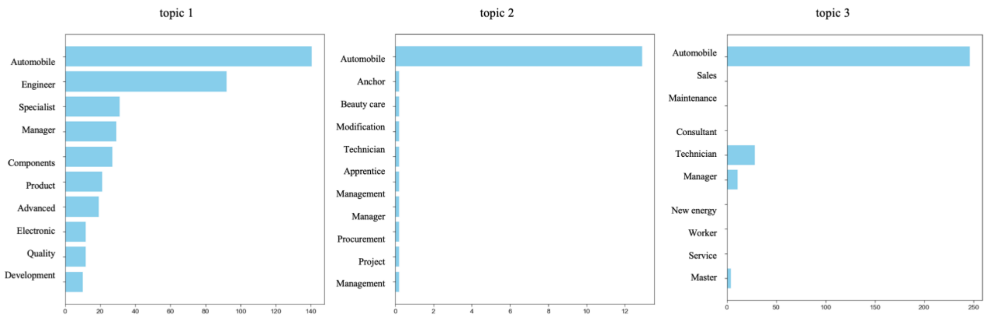

Figure 11. Topic Classification Modeling Results.

5. Research Discussion

5.1. Overview of Research Results

In terms of policy making, sentiment analysis shows that negative sentiment texts account for the highest proportion, indicating that policymaking emphasizes regulatory measures to address urgent issues such as environmental protection and energy transition, but also shows a high degree of attention to new energy and other fields. Thematic modeling analysis reveals that policy texts cover five themes, including release and implementation, new energy promotion, engineering demonstration and industrial informatization, underscoring the complexity and multi-dimensional nature of policy formulation. Sentiment analysis and topic modeling in the domains of market analysis, R&D, manufacturing, and sales services reveal distinct patterns and focal points. Positive sentiment is dominant in market analysis texts, indicating that industry development is supported; technology research and development texts are mostly positive, showing that innovation is encouraged; production and manufacturing texts are dominated by positive sentiment, which means that the manufacturing process is affirmed; and sales and service texts are dominated by negative sentiment, indicating a prevalence of customer complaints and service-related issues in this domain. In general, the sentiment distribution of texts in various fields is uneven, and the themes are diverse, covering all aspects from macro policies to specific technologies, from market dynamics to production and sales, reflecting the development status and focus of the automotive industry at different levels.

5.2. Relevant Thoughts on Industry-Education Integration

Based on the development characteristics of the automotive industry chain revealed by empirical research, this paper suggests optimizing the talent training system from six dimensions. At the policy response level, we should focus on strengthening the cultivation of policy interpretation and implementation capabilities, integrate policy practice content such as carbon emission trading and battery recycling by incorporating dedicated courses on new energy vehicle regulations and policy implementation, and establishing policy simulation labs in parallel, and use environmental compliance case libraries and industrial information sandbox simulations to deepen students' understanding of the rationale behind policy decisions. In view of the normative constraint characteristics revealed in policy texts, a dynamically updated industry standard tracking mechanism can be established to transform policy documents from the Ministry of Industry and Information Technology and other relevant authorities into structured case libraries, and cultivate students' ability to convert policy requirements into technical standards.

Technical research and development education needs to closely follow the industry's innovation needs, build a micro-professional cluster covering the core technologies of intelligent driving, and with an emphasis on core technologies such as automotive-grade chip design, V2X communication standards, and intelligent systems integration. Through joint establishment of pre-research labs with industry leaders like CATL and introducing a patent incubation workshop model, students can participate in real technical research in cutting-edge fields such as solid-state batteries and hydrogen fuels. At the same time, a technical roadmap simulation project is set up to train students to grasp the laws of technical iteration and deeply connect the new energy fields of policy concern with technical research and development.

The intelligent manufacturing training system should focus on improving digital practical ability, creating a digital twin factory that integrates MES system and industrial robots, so that students can master the core skills of intelligent manufacturing in scenarios such as virtual debugging and process optimization. In view of the positive evaluation characteristics of the production link, a lean production simulation course covering the four major processes of stamping, welding, painting, and assembly is developed, and the application ability of tools such as SPC and FMEA is strengthened through the quality traceability sandbox system, thereby aligning talent development precisely with the quality control requirements of manufacturing processes.

Market service education urgently needs to break through the innovative model. In view of the high negative feedback in the sales service field, a practical simulation system for new automotive retail is developed, integrating digital service scenarios such as user portrait construction and omni-channel marketing. A customer experience innovation studio is established to focus on cultivating new capabilities such as user journey design and service touchpoint optimization. At the same time, an after-sales big data analysis platform is built to develop skills in fault prediction and spare parts management using real maintenance data, and effectively improve students' practical level in solving service pain points.

The interdisciplinary training mechanism needs to break professional barriers, create a three-dimensional curriculum system that integrates policies, technologies, and markets, and implement an interdisciplinary project mentor system through industrial innovation experimental classes. Implement dual-track credit certification, allowing students to obtain both engineering technology and management and operation certificates, and carry out full industry chain simulation training covering R&D, production, and sales to cultivate compound talents who are familiar with both battery technology and carbon management practices.

The construction of a dynamic adjustment mechanism is essential for ensuring the long-term sustainability and responsiveness of the training system. It is necessary to establish an industry demand radar system to capture the technological trends in emerging fields such as smart cockpits and vehicle-road collaboration in real time. Set up a fast iteration channel for courses, implement emergency course development for sudden technological changes such as hydrogen energy storage, and at the same time, through the analysis of student learning behavior data, build a personal ability growth portrait, realize dynamic optimization of the training program, and ensure that education supply and industrial changes resonate at the same frequency.

6. Conclusion

This study systematically analyzed the text data of the automotive industry chain through natural language processing technology, revealing the emotional distribution and theme characteristics of each link of policy, market, technology, production and service, and providing a data-driven decision-making basis for the innovation of the industry-education integration education path. On the theoretical level, by introducing NLP technology, the interdisciplinary perspective of industry-education integration research has been expanded; on the practical level, the proposed six-dimensional optimization scheme can effectively solve the problems of lagging curriculum system and insufficient school-enterprise collaboration, and help the synchronous iteration of educational content and industry dynamics. Future research can further expand the data coverage, explore the fusion analysis of multimodal data, and strengthen the application of NLP models in personalized education recommendations. In addition, the continuous optimization of the dynamic adjustment mechanism will promote the adaptability of the industry-education integration education system and inject long-term impetus into the high-quality development of the automotive industry.

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