Modern Economy, 2025, 16(11), 1827-1835
https://www.scirp.org/journal/me
ISSN Online: 2152-7261
ISSN Print: 2152-7245

Generative AI-Driven Business Value Insights in Industry Report Development: A Case Study of AI Education Sector Reports

Junsong Chen

Nanjing Foreign Language School, Nanjing, China
Email: Chenjunsong3936@126.com

How to cite this paper: Chen, J. S. (2025). Generative AI-Driven Business Value Insights in Industry Report Development: A Case Study of AI Education Sector Reports. *Modern Economy, 16,* 1827-1835.
https://doi.org/10.4236/me.2025.1611084

Received: May 24, 2025
Accepted: November 10, 2025
Published: November 13, 2025

Abstract

In recent years, the application of Generative Artificial Intelligence (GAI) technology has rapidly expanded in the fields of knowledge production, text generation, and information analysis. Particularly in industry research and business consulting scenarios, GAI is increasingly regarded as an important tool for enhancing information integration efficiency and insight quality. This paper takes the AI education industry as an example to explore the application logic, methodological pathways, and theoretical significance of GAI in industry report R & D. By introducing an extended PESTMI (Political, Economic, Social, Technological, Market, Industry) analysis framework, combined with Prompt Engineering and multi-tool collaboration strategies, this paper constructs a human-machine collaborative report generation model and analyzes its advantages and limitations in structured writing, data analysis, and knowledge integration. Research indicates that GAI can effectively enhance the speed and topic coverage of initial draft generation for industry reports; however, it still requires human intervention and knowledge graph assistance in areas such as fact-checking, data citation, and deep insight generation. Theoretically, this paper further discusses how GAI reshapes the knowledge production mechanism and proposes a future knowledge governance path of "algorithm-human co-creation" for industry report R & D.

Keywords

Generative Artificial Intelligence, Industry Report, AI Education, PESTMI Framework, Prompt Engineering, Business Model Analysis, Social Structure, User Behavior

1. Introduction

The application potential of Generative Artificial Intelligence in fields such as accounting, statistics, and business has been widely recognized. Industry reports, as systematic analyses of specific industries, directly impact the effectiveness of corporate strategic decisions and social resource allocation (Dwivedi et al., 2023). However, traditional report R&D processes suffer from issues such as "time-consuming information collection, low data integration efficiency, and strong analytical subjectivity," particularly lacking systematic observation tools for soft dimensions like social structure changes and market behavior evolution.

Generative Artificial Intelligence, through Large Language Models (LLMs) trained on large-scale corpora, possesses the ability to extract patterns from unstructured text, reorganize information, and perform semantic generation. This capability not only changes the way knowledge is generated but also prompts a transformation in industry research from "human-driven information integration" to "human-machine collaborative cognitive co-creation." From a theoretical perspective, the introduction of GAI renders the knowledge production process 'semi-automated,' meaning algorithms learn structured knowledge during the pre-training phase, which is then verified and corrected by human experts. This model aligns with the internal logic of "knowledge co-construction" and "cognitive extension" theories in sociology.

Furthermore, the application of GAI in industry research represents not only a tool-level change but also a reconstruction of the knowledge governance system. On one hand, generative models reconstruct the industry cognitive system through probabilistic statistics, shifting report writing from experience-driven to data-driven. On the other hand, the interpretability, authenticity, and ethical risks of model outputs also raise new research questions. Therefore, systematically exploring the application framework and theoretical significance of GAI in industry report R&D holds significant practical value and academic inspiration.

Based on an interdisciplinary perspective combining business and sociology, this paper systematically explores the application potential of GAI (using DeepSeek as an example) throughout the entire process of industry research report writing. The research not only focuses on its technical efficacy in information processing and content generation but also emphasizes analyzing how it assists researchers in exploring soft topics such as business model deconstruction, social stratification impact analysis, and user behavior insight. Through the case study of the AI education industry, it evaluates its practical pathways and limitations in interdisciplinary research.

The innovations of this paper are mainly reflected in three aspects: (1) Proposing a cognitive mechanism model for GAI in industry report R & D from the perspective of knowledge production theory; (2) Constructing a report generation process based on the extended PESTMI framework; (3) Validating the feasibility of the model in report R & D through practical cases, providing theoretical and methodological references for the automation of industry research.

The model used in this study, DeepSeek V3.2, is an AI model that is completely free for research and commercial use. DeepSeek was trained on a massive and diverse dataset, and the primary language used in its training was English, meaning that a very large part of its knowledge and capabilities are built upon English text. However, it was also extensively trained on a significant amount of Chinese data, making it highly capable in both languages. Therefore, this study adopts DeepSeek V3.2 as the core generative tool to ensure cross-lingual performance and reproducibility of the research process.

2. Theoretical Basis and Research Framework

2.1. Theoretical Basis

The research foundation of Generative Artificial Intelligence can be traced back to the intersecting development of Natural Language Processing (NLP) and Machine Learning. The Neural Language Model proposed by Bengio et al. provided the mathematical foundation for semantic generation, while the Transformer architecture (Vaswani et al., 2017) enabled global modeling with context dependency, allowing language models to generate long texts with logical coherence. From a knowledge production perspective, the role of GAI is not merely a text reproduction tool but rather a "symbolic creation system." Its core lies in reorganizing existing knowledge through probabilistic reasoning to generate new semantic associations.

From the perspective of Social Constructivism (Berger & Luckmann, 1966), knowledge production is essentially a process of social interaction. GAI, through corpus learning and semantic generation, achieves "algorithm-driven reproduction of social consensus." This means that while machines simulate human knowledge construction, they are also reshaping the social distribution structure of knowledge. Although its output originates from existing data, the re-semantization process can generate "latent knowledge." Therefore, in industry report generation, the value of GAI lies not only in time savings but also in promoting cross-domain knowledge integration and cognitive transfer.

Furthermore, from a cognitive science perspective, GAI's prompt engineering can be seen as "external cognitive scaffolding." When researchers control model output through prompts, they are essentially translating human thought patterns into machine reasoning instructions. This process corresponds to the "Extended Mind Theory" proposed by Clark (2016), where humans and artificial systems together constitute a cognitive whole. Thus, GAI is not just an auxiliary tool but an integral part of the cognitive process.

2.2. Extended PESTMI Framework

PEST analysis is a classic macro-environmental analysis tool in industry research, used to identify external environmental factors such as Political (P), Economic (E), Social (S), and Technological (T). This paper adds two new dimensions, Market (M) and Industry (I), to form the extended PESTMI framework.

The theoretical basis for this framework lies in Systems Theory and Complexity Science. The evolution of industrial ecosystems is often influenced by the interaction of multiple factors, making it difficult for a single dimension to fully depict the industry structure. The M dimension (Market) focuses on demand, competition, and consumer behavior; the I dimension (Industry) focuses on the industrial chain, resource allocation, and collaborative innovation. Together, they complement the shortcomings of the traditional PEST model at the level of economic activity, making it more aligned with the dual needs of business and social analysis.

Furthermore, the introduction of the PESTMI framework also resonates with Socio-Technical Systems (STS) theory. This theory posits that any technological application is embedded within social relations and institutional environments. Therefore, in the R & D of industry reports assisted by Generative AI, multi-layered interactions exist among political systems, economic environments, social values, and technological conditions, necessitating a holistic analysis from a systems perspective.

3. Research Methods

This paper adopts a composite research method of "Prompt Engineering + Multi-tool Collaboration + Human Review."

Methodologically, this research follows a constructive research paradigm, exploring the practical utility of GAI through a combination of theoretical deduction and case validation. The research process includes the following steps:

Corpus Construction: Select the AI education industry as the research object, collect policy documents, industry reports, patent data, and investment/financing information from 2019-2025 to build a basic corpus.

Prompt Engineering Design: Design structured prompt templates for the six dimensions of PESTMI to control the logical hierarchy and semantic depth of model generation.

Model Operation and Multi-tool Collaboration: Use the DeepSeek model to generate the initial draft and perform cross-validation through databases such as Duojing Education Research Institute (2025), National Bureau of Statistics, and Baidu Index.

Human Verification and Evaluation Indicators: Quantitatively evaluate the generated results using four indicators: factual accuracy rate, information coverage rate, time saving rate, and logical consistency.

This research particularly emphasizes the knowledge co-construction process of human-machine collaboration. GAI is responsible for macro-framework generation and semantic organization, while researchers perform data verification and insight deepening in the later stages. This process reflects the knowledge governance logic of "algorithm-human complementarity," where machines excel at finding patterns in vast information, and humans excel at value judgment and semantic interpretation.

4. Construction of GAI-Based Industry Research Framework: Taking PESTMI as an Example

An industry report is a form of literature that systematically analyzes and researches the market conditions, development trends, competitive landscape, etc., of a specific industry. Industry reports are generally generated according to the PEST framework system. PEST is a model used for macro-environmental analysis, including Political, Economic, Social, and Technological aspects. This analysis framework, on one hand, is applicable to the analysis of almost all industries; on the other hand, it also suffers from common problems such as insufficient deconstruction of the industrial ecosystem and lack of quantification.] Therefore, it is necessary to revise the PEST framework for the analyzed industry and address the lack of quantification under the revised framework. This paper takes the AI education industry report as an example to revise the PEST framework.

GAI has obvious advantages in the generation and revision of frameworks. Select excellent research reports on AI education from previous years, input them as attachments into GAI, taking DeepSeek as an example, and provide the prompt: "Please summarize the research framework for AI education from the attachments." However, the output from DeepSeek was optimized from the paragraph names in the attached reports. Although the results generated each time were inconsistent, most covered PEST elements, but the textual expressions were not necessarily Policy, Economy, Society, and Technology. Therefore, the prompt was optimized to: "Please refer to the attached reports and extend the AI education research framework from PEST to more dimensions" (Li et al., 2025). DeepSeek provided the PESTMI analysis framework, which added two dimensions, Market (M) and Industry (I), to the original four. The PESTMI framework covers the core elements of market and industry in business analysis and provides structural space for sociological perspectives (such as technology adoption, digital divide). Market refers to the different segmented tracks and scale of AI education; Industry refers to the analysis of different levels of enterprises, market size, business models, market competition landscape, etc., within the industry. This PESTMI framework not only covers the core market and industry elements in business analysis but also provides structural space for integrating sociological research perspectives on AI technology adoption, digital divide, and social equity.

5. Industry Report Generated Based on the New Framework

5.1. Prompt Engineering: Task Instruction Design Based on PESTMI

Prompts are the core instructions for GAI to understand tasks, requiring both structural clarity and demand extensibility. For the AI education industry report, three types of typical prompt templates are designed.

(1) Framework Generation Type (Full-Dimension Coverage)

Instruction Example: "Based on the PESTMI framework, generate a macro-analysis report framework for the AI education industry in 2025, requiring inclusion of 'P (Policy: Key policies 2019-2025), E (Economy: Investment/Financing + Market Size), S (Society: Awareness + User Profile), T (Technology: Patent Trends + Typical Products), M (Market: Global/China Segmented Track Size), I (Industry: Enterprise Classification + Business Models)' six sections, with 3 - 5 subthemes under each section."

Output Characteristics: Quickly generates a structured framework, but the content tends to be programmatic, requiring further refinement.

(2) Single-Dimension Deepening Type (Taking M, I as Examples)

M Dimension (Market): "Predict the market size of China's AI education from 2025 to 2028, requiring inclusion of 'Compound Annual Growth Rate (CAGR), driving factors (policy/technology/demand), proportion of segmented fields (smart hardware/online courses/adaptive systems)', and generate a market size trend line chart (Markdown code)."

I Dimension (Industry): "Analyze the competitive landscape of enterprises in the AI education industry, categorized by 'Pure AI Tech Companies (e.g., Squirrel AI), Traditional Education Companies adopting AI (e.g., New Oriental), Hardware + Service Providers (e.g., Xuewei Technology)', dissecting the leading enterprises, core products, and business model canvas for each type." (Porter, 1980)

Output Characteristics: Can generate "simulated" data and industry maps, but authenticity requires cross-validation with external tools (e.g., Li et al., 2025; Duojing Education Research Institute, 2025).

(3) Data Supplement Type (Cross-Dimension Linkage)

Instruction Example: "Combining the Ministry of Education's 2025 'Pilot Management Measures for AI Education Applications' (P dimension), analyze its impact on the ToG smart education market (M dimension) and corporate compliance requirements (I dimension), supplement with pilot city lists (e.g., Beijing, Shanghai, Shenzhen) and corresponding policy subsidy amounts."

Output Characteristics: Rich in heuristic content, but precise data such as "subsidy amounts" require manual verification on the Ministry of Finance website.

(4) Business-Society Cross-Analysis Type (Bourdieu, 1986)

Instruction Example: "Analyze how the popularization of AI education technology affects the academic performance of students from different family socioeconomic backgrounds, and explore the mechanisms through which it may exacerbate or alleviate educational inequality, proposing suggestions from the perspectives of social capital and business promotion models."

Output Characteristics: GAI can identify surface phenomena such as "urban-rural differences" and "income stratification," but its explanatory power for deeper social mechanisms like "cultural capital" and "social reproduction" is insufficient, requiring researchers to introduce sociological theories for in-depth interpretation.

5.2. Step-by-Step Decomposition and External Tool Collaboration

Prompt engineering can enhance content targeting but suffers from issues like "insufficient word count, data distortion, lack of charts." Therefore, a strategy of "dimension-by-dimension decomposition + external data injection + AI secondary generation" is adopted, this requires us to combine AI-generated content with human research in a complementary way, which means we should focus primarily on what aspects AI isn't good at and make up for them by adding human-generated content. Taking the PEST four dimensions as an example:

(1) Political (P): AI Auto-Generation + Human Verification

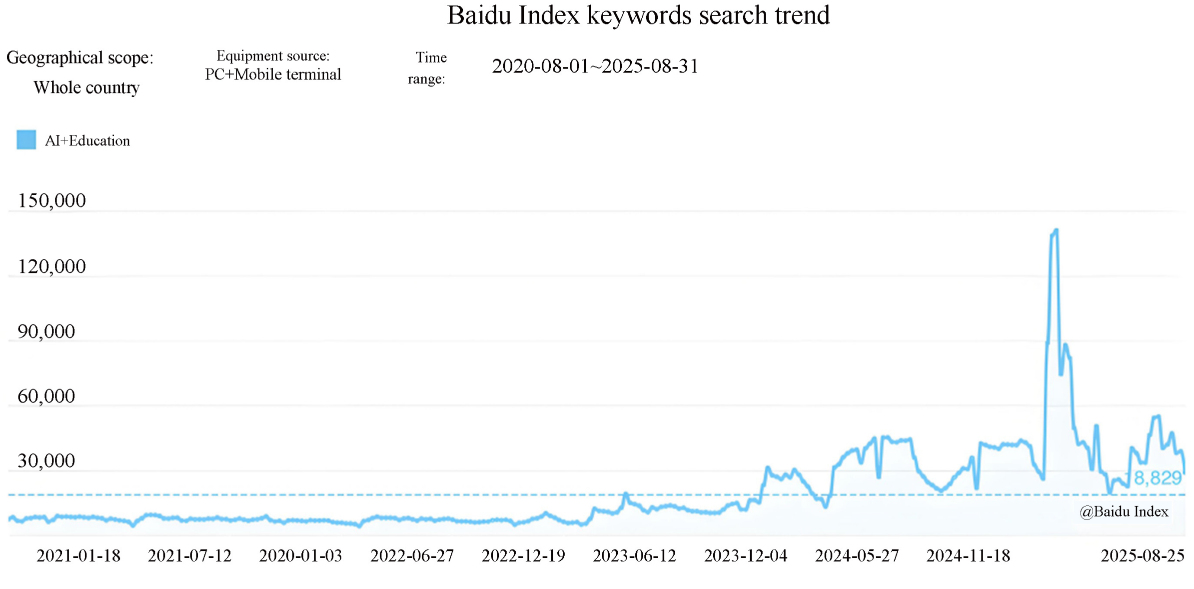
Instruction (What we asked the model): "Please analyze AI education policies from 2019-2025, supplement with 2025 new policies (e.g., 'Pilot Management Measures for AI Education Applications'), organize into a table according to 'Policy Time-Issuing Authority-Core Content', and interpret the policy impact on 'curriculum system, teacher training, corporate compliance'."

Output: Generates a table containing 7 policies, with an 85% match between policy text and publicly available information on the Ministry of Education website, but the "impact interpretation" is macro-level, requiring manual supplementation of micro-data like "a 30% increase in the number of pilot schools in a certain province".

(2) Economic (E): External Data-Driven + AI Analysis

Steps: ① Call Duojing (Duojing Education Research Institute, 2025) (an online database and commercial service website), API to obtain real investment/financing data for AI education in 2025 (e.g., "Q1 financing events increased 15% year-on-year, early-stage projects accounted for 60%"); ② Input instruction: "Combining Duojing 2025 data (Duojing Education Research Institute, 2025), analyze AI education investment/financing trends (round distribution, regional differences, hot sectors), and generate a bar chart (Markdown code)."

Output: AI generates a "financing round distribution table" and bar chart code, but the analysis of "regional differences" (e.g., first-tier cities vs. lower-tier markets) is superficial, requiring manual supplementation of details like "the proportion of financing for AI self-study rooms in lower-tier markets has increased".



(3) Social (S): Tool Quantification + AI Interpretation

Steps: ① Capture the popularity of the keyword "AI education" via Baidu Index (2020.1.1-2025.8.31), obtaining key node data (e.g., April 2024: 42,103 → February 2025: 140,912); ② Input instruction: "Interpret the driving factors (policy, technology, social events) behind the surge in 'AI education' search volume, and correlate with user profiles (age, occupation, region)."

Output: AI generates a "popularity-event correspondence table," but the correlational analysis of "social events" (e.g., a celebrity endorsing an AI learning device) is superficial, requiring manual supplementation of data like "search volume increase among target users (parents aged 25 - 35) after endorsement".

(4) Technological (T): AI + Patent Data Fusion

Steps: ① Call the Chinese patent database to obtain the number of AI education technology patent applications from 2020-2025 (e.g., "Natural Language Processing patents increased 25% annually"); ② Input instruction: "Combining patent data, analyze R & D hotspots in AI education technology (algorithm optimization, hardware adaptation, content generation), and generate a line chart (Markdown code)."

Output: AI generates technology trend analysis, but the interpretation of "hardware adaptation" (e.g., iteration of AI chips in learning devices) relies on training data, requiring manual supplementation of details like "performance parameters of the AI chip installed in a certain brand's new learning device in 2025".

6. Conclusion: The New Paradigm of Industry Report R & D Driven by GAI

Generative Artificial Intelligence brings revolutionary changes to industry report R & D. Its advantages in areas such as agile framework generation, policy text supplementation, (and cross-domain knowledge inspiration involving commercial and social factors) significantly lower the R & D threshold and time cost. However, technological limitations dictate the necessity of "human-machine collaboration"-human researchers must lead in verifying data authenticity, judging trends, assessing business logic reliability, and conducting in-depth analysis of social impacts.

In the future, with GAI technology iteration (e.g., multimodal generation, agent collaboration), industry report R&D is expected to evolve towards a "Business-Sociology-GAI" tripartite collaboration model: by constructing a "Social Structure Agent" (analyzing inequality, digital divide), a "Business Model Agent" (simulating competition, evaluating profitability), and a "Policy Ethics Agent," GAI can be upgraded from an auxiliary tool to a core collaborative partner in interdisciplinary research.] It may also evolve towards a model of "agent autonomous tool scheduling + lightweight human intervention." For example, constructing a "Policy Analysis Agent" (automatically capturing regulation databases + generating interpretations), a "Data Verification Agent" (cross-referencing multi-source databases), and a "Visualization Agent" (autonomously generating dynamic charts) to achieve an upgrade from "auxiliary tool" to "core collaborative partner."

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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