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Research on Policy Gaps in AI-Enabled Green Governance for China's Packaging Industry Based on the PMC Model — A Case Study: AIGC Packaging Practices at Zhejiang Great Shengda Packaging Co., Ltd.

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Abstract

The packaging industry constitutes a vital component of China's manufacturing sector. By 2025, the number of enterprises above designated size in this industry will exceed 20,000, with annual operating revenue approaching 2 trillion yuan. Driven by both the "dual carbon" goals and intelligent manufacturing initiatives, the application of AI technology to enable green governance has emerged as a key pathway for industrial transformation. This study employs a mixed methodology combining policy text quantitative analysis with the PMC index model. First, we conducted word frequency analysis, co-occurrence network analysis, and thematic clustering on 47 relevant policy documents from 2018 to 2025 to reveal the structural characteristics of policy discourse. Subsequently, we constructed a PMC evaluation framework comprising nine first-level dimensions to quantitatively assess 17 core policies. Finally, we validated these findings using Great Shengda 's AIGC packaging practices alongside comparative cases, including Yutong Technology and Hexing Packaging. The study reveals that within policy texts, the two discourse clusters—"green" and "intelligent"—exhibit a distinct "dual-center–weak-linkage" pattern, with the cross-policy density between AI and green governance measuring only 0.06. The overall PMC score stands at 6.41, yet demonstrates a significant deficit in the "AI–Green Coordination" dimension, scoring merely 0.45. The research identifies three structural gaps and proposes policy recommendations, including establishing an "AI + Green" policy synergy framework, creating a dedicated fund for AI-enabled green transformation, and accelerating the development of cross-sector standard systems.

Keywords

PMC Index Model; Policy Text Quantification; Policy Gap; AI-Enabled; Green Governance; Packaging Industry; Great Shengda

I. Introduction

The packaging industry is a foundational sector of the national economy, spanning the entire lifecycle of goods, from production to distribution and consumption. According to statistics from the China Packaging Federation, in the first half of 2025, the number of enterprises above designated size in the national packaging industry reached 20,022, with cumulative operating revenue totaling 995.663 billion yuan, representing a year-on-year increase of 0.45%; total profits amounted to 43.581 billion yuan, up 5.05% year-on-year [1]. For the full year of 2025, the industry's total output value is projected to reach approximately 2.8 trillion yuan. Behind this overall growth, the industry is facing profound transformational pressures: on one hand, environmental regulations are becoming increasingly stringent that the mandatory national standard "Requirements for Restricting Excessive Packaging in Express Delivery" will officially come into effect in 2026, and the revised "Interim Regulations on Express Delivery" includes a dedicated chapter on packaging, making green governance a "hard constraint" for corporate survival; on the other hand, narrowing profit margins are compelling enterprises to seek technology-driven efficiency breakthroughs.

Meanwhile, artificial intelligence (AI) technology is deeply integrating into the packaging industry chain. Leading enterprises, exemplified by Zhejiang Great Shengda Packaging Co., Ltd. (603687. SH), have already pioneered the application of AIGC large language model technology across the entire packaging design and production workflow. In collaboration with the Institute of Information Technology at Peking University, the company has developed the "X-FUN" AIGC packaging platform, which integrates mainstream large language models such as DeepSeek and Qianwen. This platform enables end-to-end AI-driven generation for brand strategy formulation, packaging design, and technical drawing creation, reducing the number of traditional sampling cycles from 3–5 rounds to just 1–2 rounds [2]. Zhejiang Great Shengda Packaging Co., Ltd.has been successively recognized as a "Typical Case of AI-Enabled Manufacturing in Zhejiang Province" and an "Excellence-Level Intelligent Factory" by the Ministry of Industry and Information Technology (MIIT). In September 2025, it became one of the first enterprises selected for the "Zhejiang Province Zero-Carbon (Near-Zero-Carbon) Factory" cultivation program, among only six enterprises in the entire province [3]. This case illustrates a significant trend: AI technology is simultaneously driving efficiency enhancements within the packaging industry (via intelligent manufacturing) and improvements in environmental performance (via green governance) that a phenomenon best described as "AI-Enabled Green Governance."

However, leveraging AI to enable green governance cannot be achieved through the unilateral efforts of enterprises alone. It requires a policy framework to provide institutional support across multiple dimensions, such as incentives for AI technology R&D, green manufacturing standards, data-sharing mechanisms, and the

cultivation of industry-specific talent. In this context, does the existing policy framework keep pace with corporate practices? Is there a structural gap between policy provision and corporate demand? These questions constitute the central concerns of this study.

This study employs a mixed-methods design comprising "textual quantification → PMC assessment → case validation." First, textual quantification of policy documents is used to reveal the macro-level landscape of policy discourse; next, the PMC index model is applied to conduct multi-dimensional quantitative diagnostics of core policies; finally, using Great Shengda as an in-depth case study, alongside Shenzhen Yuto Packaging Technology Co., Ltd.(Yuto Packaging) and Xiamen Hexing Packaging Printing Co.(Hexing Packaging), Ltd. as comparative benchmarks, micro-level validation is performed. This approach establishes a three-tier gap analysis framework: "macro-level discourse → meso-level structure → micro-level practice."

II. Literature Review and Analytical Framework

2.1. Policy Gap Theory

The "Policy Gap" is a core concept in public policy studies. Pressman and Wildavsky (1973), in their seminal work *Implementation*, identified the "implementation gap" between policy intent and actual implementation outcomes, thereby establishing this research tradition [4]. Hill and Hupe (2002) extended gap analysis from the implementation level to the "governance gap," focusing on coordination failures within multi-level governance frameworks [5]. Howlett and Ramesh (2003), from a policy design perspective, proposed the "policy design gap," arguing that the mismatch between policy instruments and objectives constitutes a key source of policy failure [6].

In the Chinese context, Xue Lan et al. (2015) applied policy gap analysis to research on emerging industry policies, noting that the policy gap in emerging industries primarily manifests as "institutional supply lagging behind technological innovation" [7]. Chen Ling et al. (2020) further proposed that policy gaps in interdisciplinary domains (e.g.AI + environmental protection) exhibit a "dual lag" characteristic: they lag both behind the development of individual technologies and behind the emergence of integrated applications [8]. While the aforementioned studies have laid a theoretical foundation for this paper, research applying policy gap analysis to the interdisciplinary domain of "AI-enabled green governance" which particularly within the traditional manufacturing sub-sector of packaging—remains limited.

2.2. PMC Index Model

The PMC (Policy Modeling Consistency) index model was proposed by Ruiz Estrada in 2011 and has become a classic quantitative tool for policy consistency assessment

[9]. The core principle of this model is to avoid making prior judgments about the relative quality of policies; instead, it employs a multi-dimensional evaluation framework to assign standardized scores to policy documents, ultimately generating a PMC index and a radar chart that intuitively illustrate the policy's performance across various dimensions. Compared to traditional qualitative assessments, the PMC model offers the following advantages: (1) high practicality, with clearly defined scoring criteria; (2) flexible adjustability of evaluation dimensions to accommodate diverse policy domains; and (3) the visual representation provided by the radar chart, which facilitates the identification of a policy's "strengths" and "weaknesses."

Among domestic scholars, Zhang Yong'an et al. (2017) were among the first to introduce the PMC model into the field of policy analysis in China [10]; in recent years, the PMC model has been applied to policy evaluation in multiple domains, including intelligent manufacturing, green finance, new energy vehicles, and integrated circuits. This study adopts the PMC model because it is particularly well-suited for assessing the coordination of cross-domain policies which is a key requirement for analyzing the triple intersection of "AI + green + packaging."

2.3. Analytical Framework: A Three-Level Progressive Gap Identification Approach

This study establishes a "three-tier progressive" analytical framework:

First Layer — Macro-level Discourse Analysis: By employing quantitative methods for policy texts (word frequency analysis, co-occurrence network analysis, and LDA topic clustering), this layer reveals the macro-level patterns of policy discourse within a corpus comprising 47 policy documents and identifies structural characteristics at the discourse level.

Second Layer — Meso-level Structural Assessment: Using the PMC index model, we conduct quantitative scoring across nine dimensions for 17 core policies, thereby identifying gaps in operational dimensions such as tool design, incentive intensity, and coordination mechanisms.

Third Layer – Micro-level Practical Validation: Using Great Shengda , a leading enterprise in the AIGC packaging sector, as the core case study, and Yutong Technology and Hexing Packaging as comparative cases, this layer verifies the existence and impact of the aforementioned gaps from a corporate practice perspective.

The logical relationship of the three-tier analysis is as follows: text quantification provides directional guidance on "where the gaps lie," the PMC model offers a quantitative benchmark to assess "the magnitude of these gaps," and case studies elucidate the mechanisms through which "these gaps impact the enterprise." Together, these three components constitute a progressive chain of evidence.

III. Quantitative Analysis of Policy Texts

Policy texts serve as written expressions of policy intentions, embodying the cognitive frameworks and focus allocations of policymakers. Prior to proceeding to the multi-dimensional scoring in PMC, this chapter conducts a quantitative analysis of policy texts across a broader scope, revealing the structural characteristics of policy discourse through three dimensions whcih are word frequency distribution, co-occurrence networks and thematic clustering, thereby providing a "macro-level map" for subsequent gap identification.

3.1. Construction of the Policy Document Repository

3.1.1. Search strategy

To encompass the interdisciplinary domain of "AI-empowered green governance," this study employs a layered retrieval strategy (see Table 1).

Table 1. Policy Text Hierarchical Retrieval Strategy

Search level	Search keyword combination	Retrieval field	Target
Core Cross-Layer	"Artificial Intelligence" AND "Green" AND "Packaging"	Full text	Direct correlation
AI + Manufacturing Layer	"Artificial Intelligence" OR "Intelligent Manufacturing" OR "Digitalization" AND "Manufacturing Industry"	Title/Keywords	AI Policy Domain
Green + Packaging Layer	"Green" OR "Low-carbon" OR "Dual Carbon" AND "Packaging" OR "Express Delivery"	Title/Keywords	Green Policy Domain
Basic Policy Layer	"Artificial Intelligence", "Intelligent Manufacturing", "Green Manufacturing", "Circular Economy"	Title	Strategic Framework

The search databases include: the Policy Document Database of the State Council of the People's Republic of China, the Policy Document Database of the Ministry of Industry and Information Technology, the Policy Document Database of the National Development and Reform Commission, the Policy Document Database of the Ministry of Ecology and Environment, the Policy Document Database of the State Post Bureau, and the "Beida Law Database." The time span is set from January 2018 to December 2025. The rationale for selecting 2018 as the starting year is that in 2017, the State Council issued the "Development Plan for New Generation Artificial Intelligence," and 2018 marked the first full policy year following the elevation of AI to a national strategy.

3.1.2. Screening Procedure and Results

The retrieved literature was screened according to the following procedure: (1) remove duplicates (i.e.,), the same document appearing in multiple databases); (2) exclude documents that merely mention the keywords but lack substantive provisions (e.g.,, speeches by leaders, press releases, general work notices); (3) exclude purely local-level policy documents (to be addressed in subsequent extended research). Ultimately, 47 national-level policy documents were obtained, forming a quantitative corpus of policy texts.

Building on this foundation, we further screened 17 policies that are "directly

relevant" to AI-enabled green governance in the packaging industry, using them as the core sample set for subsequent PMC scoring. The screening criteria were as follows: the policy content must substantially pertain to the packaging industry, or, while not exclusively limited to the packaging industry, must be clearly applicable to it, and must address at least one of the following two domains: "AI/Digitalization" or "green governance."

Table 2. Composition of the Policy Text Database

Class	Quantity	Examples of representative policies
AI/Digitalization Policies	14 items	"Development Plan for Next-Generation Artificial Intelligence", "14th Five-Year Plan for Intelligent Manufacturing Development", "Three-Year Action Plan for 'Data Factor ×' (2024–2026)"
Green/Dual Carbon Policy	16 items	Guiding Opinions on Accelerating the Green Development of the Manufacturing Sector" and "Implementation Plan for Achieving Carbon Peaking in the Industrial Sector"
Specialized Policies for the Packaging Industry	8 items	"Action Plan for Further Advancing the Green Transformation of Express Delivery Packaging" and "Requirements for Restricting Excessive Packaging in Express Delivery" — Mandatory National Standards
Cross-cutting policies	6 items	"Pilot Program for the Application of Intelligent Manufacturing Standards" and "Action Plan for Digital Transformation of the Manufacturing Industry"
Regulations/Standards	3 items	Revised *Provisional Regulations on Express Delivery* (including a dedicated chapter on packaging)
Amount to	47 items	

3.1.3. Text Preprocessing

Text preprocessing was performed using Python 3.11: the jieba word segmentation library was employed for Chinese word segmentation; a custom dictionary for the packaging industry was constructed, comprising 137 professional terms which including "AIGC," "zero-carbon factory," "green packaging," "smart factory," "circular utilization," "degradable materials," and "industrial internet", to ensure segmentation accuracy; the HIT stop-word list was used to remove stop words; part-of-speech tagging was then applied to extract lexical items (e.g.,), nouns, verbs, gerunds) for subsequent analysis. After preprocessing, approximately 174,000 valid lexical units were obtained.

3.2. High-Frequency Word Analysis

3.2.1. Overall high-frequency word distribution

We conducted word frequency analyses on the full-text corpora of 47 policies. After excluding common administrative terms such as "policy," "department," "agency," "related," "further," and "active," we extracted the top 50 high-frequency content words. Table 3 presents the top 30 high-frequency words.

Table 3. Top 30 High-Frequency Terms in Policy Documents

Ranking	Keywords	Word Frequency	Frequency(‰)	Ranking	Keywords	Word Frequency	Frequency(‰)
1	green	3,247	18.62	16	technology	892	5.11
2	develop	2,891	16.58	17	intelligence	876	5.02
3	enterprise	2,456	14.08	18	standard	845	4.84
4	make	2,103	12.06	19	Recycling	812	4.66
5	pack	1,978	11.34	20	express delivery	789	4.52
6	digitalize	1,654	9.48	21	energy conservation	743	4.26
7	carbon emission reduction	1,532	8.78	22	Transformation	721	4.13
8	artificial intelligence	1,421	8.15	23	material	698	4.00
9	carbon	1,387	7.95	24	terrace	667	3.82
10	resource	1,256	7.20	25	recurrence	654	3.75
11	bring forth new ideas	1,198	6.87	26	Emissions	632	3.62
12	environmental protection	1,145	6.56	27	industry	618	3.54
13	system	1,087	6.23	28	design	587	3.37
14	data	967	5.54	29	Energy	554	3.18
15	apply	934	5.36	30	monitor	521	2.99

The aforementioned word frequency distribution reveals a three-tiered policy discourse structure:

First tier: core discourse terms (word frequency ≥11‰). The "green" (18.62‰), "development" (16.58‰), "enterprise" (14.08‰), "manufacturing" (12.06‰), and "packaging" (11.34‰) constitute the "first tier" of policy discourse. Notably, "packaging" has entered the core circle with a frequency of 11.34‰, indicating that the packaging industry is no longer in the "peripheral zone" of policy discourse, but has instead become a prominent focus of policy attention.

Second layer: Two major supporting discourse themes (word frequency: 7–10‰). "Digitalization" (9.48‰), "emission reduction" (8.78‰), "artificial intelligence" (8.15‰), and "carbon" (7.95‰) constitute two relatively independent supporting clusters—digitalization/AI discourse and green and low-carbon discourse.

Third layer: instrumental and operational discourse (word frequency <7‰). The lexical density of terms related to specific implementation tools and operational procedures—such as "standard" (4.84‰), "platform" (3.82‰), "design" (3.37‰), and "monitoring" (2.99‰)—has declined markedly, indicating a "gap" in policy discourse between "strategic declarations" and "operational tools."

A key structural question has emerged: while "artificial intelligence" (1,421 occurrences) and "green" (3,247 occurrences) both appear frequently, do they "encounter" each other within the same policy context, or do they operate

independently? This warrants further examination through co-occurrence network analysis.

3.2.2. Diachronic Evolution of High-Frequency Words (2018–2025)

To capture the dynamic evolution of policy discourse, Table 4 presents the historical trends in the word frequencies of key high-frequency terms.

Table 4. Annual Changes in Word Frequency of Key High-Frequency Terms (2018–2025)

A particular year	Number of policies	Frequency of the term "Artificial Intelligence"	Frequency of the term "green"	Frequency of the term "digitalization"	The co-occurrence of "smart" and "green"
2018	4 items	187	321	123	3
2019	3 items	142	256	98	2
2020	5 items	198	412	176	5
2021	7 items	276	534	231	9
2022	6 items	245	498	209	8
2023	8 items	203	542	254	11
2024	8 items	112	451	243	7
2025	6 items	58	233	187	4

The time-series analysis reveals three key characteristics:

First, the frequency of the term "artificial intelligence" peaked in 2021 (276 occurrences) and has declined annually thereafter, reaching only 58 occurrences in 2025. This trend does not signify a diminished importance of AI; rather, it more likely reflects a shift in policy discourse, from a "strategic positioning phase" to a "scenario implementation phase" where AI is no longer frequently discussed as a standalone topic, but is instead embedded within specific provisions of industry policies. In contrast, the frequency of the term "digitalization" has consistently remained high, ranging between 187 and 254 occurrences from 2023 to 2025, indicating that "digitalization," as a broader policy framework, exhibits greater continuity and pervasive influence.

Secondly, the frequency of the term "green" reached its peak in 2023 (542 occurrences), closely aligning with policy events such as the release of the *Action Plan for Further Advancing the Green Transformation of Express Delivery Packaging*; thereafter, the frequency declined slightly.

The third and most critical indicator is the co-occurrence frequency of "intelligence" and "green" within the same sentence. This metric rose gradually from 3 occurrences in 2018 to 11 occurrences in 2023, before declining to 4 occurrences in 2025. Over the eight-year period, the total number of such co-occurrences was only 49, meaning that among the 47 policies examined, each policy was discussed in conjunction with both "intelligence" and "green" on a sentence level an average of only once. Given that the policies selected in this study are primarily concentrated in two domains which are AI/digitalization and green governance, this low

co-occurrence frequency underscores the degree of separation between these two discursive domains.

3.3. Co-occurrence Network Analysis

3.3.1. Analysis Method

Using the NetworkX library in Python, we constructed a keyword co-occurrence matrix. With paragraphs serving as the co-occurrence window (the 47 policies were divided into 2,847 paragraphs), we extracted the top 80 keywords with a minimum occurrence frequency of 50, calculated the co-occurrence frequencies of each pair of keywords within the same paragraph, and then built an 80×80 co-occurrence matrix. The Louvain community detection algorithm was employed for network clustering, and Gephi 0.10 was used for visualization. The statistical significance of the community partitioning was assessed using the modularity (Q) value.

3.3.2. Overall Network Architecture

Table 5. Overall Statistical Indicators of the Keyword Co-occurrence Network

Metric	Numeric value	Interpretation of the Connotation
Number of nodes	80	Number of keywords included in the analysis
Edge count	1,247	Number of co-occurrence relationships between keywords
network density	0.395	The density of discourse is moderate to high, and the policy discourse framework is generally well-established.
Average clustering coefficient	0.672	It exhibits distinct community structural characteristics.
Modularity (Q-value)	0.483	When Q > 0.3, the community partitioning is statistically significant.
Average path length	1.89	The average number of steps required to reach any two keywords is less than 2.
network diameter	4	The maximum distance between any two keywords is 4 steps.

A network density of 0.395 indicates that the "linguistic architecture" of policy discourse has already reached a relatively mature stage, with rich interconnections among key terms. However, this metric may obscure structural differentiation among communities—therefore, further community discovery analysis is warranted.

3.3.3. Community Discovery Results

The Louvain algorithm identified three primary discourse communities, and a modularity value of Q=0.483 indicates that the community structure is well-defined and statistically significant.

Table 6. Composition and Characteristics of the Three Discursive Communities

Community	Researcher's designation	Number of nodes	Core keywords (top 8 by PageRank score)	Internal edge density	Interpretation

Community A	Green Governance Discourse Cluster	32	Green, emission reduction, carbon, resources, environmental protection, recycling, circular economy, emissions	0.743	Policy discourse centered on environmental performance
Community B	Intelligent/AI Discourse Cluster	28	Digitalization, artificial intelligence, data, intelligence, applications, platforms, algorithms, 5G	0.681	Policy discourse centered on technology-driven approaches
Community C	Institutional/Standard Discourse Cluster	20	Standards, frameworks, regulations, oversight, evaluation, certification, demonstration projects, and pilot programs	0.592	Policy discourse centered on institutional norms

The intra-community edge densities for the three communities are 0.743, 0.681, and 0.592, respectively, indicating that the intra-community discourse connectivity is considerably high; specifically, the green discourse clusters exhibit the highest degree of intra-cluster clustering, suggesting that green policies have established robust mutual citations and conceptual linkages. However, this internal cohesion may also imply insufficient connectivity between the communities.

3.3.4. Inter-community bridging analysis: dual-centre–weak-linkage pattern

Table 7. Comparison of inter-community connectivity strength

The community regarding	Number of connecting edges	Bridge keywords (top 3 by intermediate centrality)	Average edge weight	Connection Strength Evaluation
A↔B (Green ↔ Intelligent)	47	Enterprise (0.187), Manufacturing (0.162), Transformation (0.094)	1.34	Weak
A↔C (Green ↔ System)	112	Standard (0.243), System (0.198), Evaluation (0.112)	2.87	Strong
B↔C (Intelligence ↔ Institutions)	89	Standard (0.215), Pilot (0.143), Application (0.127)	2.41	stronger

Table 7 clearly illustrates the "Dual-Core Weak-Tie" pattern of policy discourse:

First, there are only 47 connecting edges between the green discourse cluster (A) and the intelligent discourse cluster (B), accounting for 3.8% of the total 1,247 edges. In stark contrast, there are 112 connecting edges between green discourse and institutional discourse (C), and 89 connecting edges between intelligent discourse and institutional discourse. This indicates that institutional/standard discourse serves as the primary "integrator" within the current policy framework; however, it primarily integrates the combinations of "green + standard" and "intelligent + standard," rather than the cross-directional combination of "green + intelligent."

Second, the average edge weight between A↔B is only 1.34, meaning that the bridging keywords co-occur an average of approximately 1.34 times per instance which significantly lower than the values of 2.87 for A↔C and 2.41 for B↔C. This indicates that even when "green" and "intelligent" appear within the same paragraph, their co-occurrence strength remains markedly weaker.

Third, greater caution is warranted regarding the nature of the bridging keywords. The bridging keywords between A↔B "enterprise," "manufacturing," and "transformation"—are all highly abstract, general concepts. In contrast, the bridging keywords for A↔C "standard," "system," and "evaluation," as well as those for B↔C

"standard," "pilot," and "application", all carry clear institutional operational implications. The connection between "green" and "intelligent" remains confined to abstract assertions such as "enterprises need to transform" and "the manufacturing sector requires intelligence and greenness," lacking substantive cross-domain concepts such as "AI-driven green design standards" or "intelligent manufacturing carbon emission evaluation frameworks."

3.3.5. Central analysis: Who is the "bridge" ?

Table 8. Top 10 Keyword Centrality Indicators

Ranking	Keywords	Degree centrality	Approaching centrality	Intermediate centrality	Affiliated Community
1	develop	0.924	0.929	0.152	Global Bridging
2	enterprise	0.886	0.893	0.138	Global Bridging
3	green	0.873	0.881	0.127	A
4	make	0.848	0.857	0.119	Global Bridging
5	standard	0.823	0.842	0.143	C
6	digitalize	0.797	0.824	0.091	B
7	system	0.785	0.813	0.104	C
8	technology	0.764	0.795	0.088	B
9	carbon emission reduction	0.752	0.782	0.072	A
10	bring forth new ideas	0.741	0.773	0.081	Global Bridging

Betweenness Centrality measures to what extent a node serves as a "must-pass node" along the shortest paths between other nodes. Table 8 shows that the "Standard" category exhibits a higher betweenness centrality value (0.143) than the "Digitalization" (0.091) and "Emission Reduction" (0.072) categories, indicating that institutional keywords play a more prominent bridging role within the overall network. However, as previously noted, this bridging effect is primarily concentrated along the "Green ↔ Institutional" and "Smart ↔ Institutional" axes, without effectively bridging the gap between "Green" and "Smart."

The four overarching bridging terms—"development," "enterprise," "manufacturing," and "innovation", exhibit relatively high intermediate and central centrality; however, they are all semantically broad, general-purpose terms. Within the network, they function similarly to "transportation hubs", characterized by high traffic volume but without necessarily pointing in a specific direction, thus failing to compensate for the absence of specialized intersectional concepts such as "AI + green."

3.4. Thematic Cluster Analysis

3.4.1. LDA Model Configuration

We applied the Latent Dirichlet Allocation (LDA) topic model to all 2,847 paragraphs across 47 policy documents for topic modeling. Using perplexity and

topic coherence as evaluation metrics, cross-validation identified the optimal number of topics as K=6. Each topic was represented by the top 10 most frequent feature words, and the topics were named by the researchers based on the semantic meaning of these feature words.

3.4.2. Six Key Policy Themes

Table 9. LDA topic modeling results—six major policy themes

Subject Number	Researcher's designation	Top 10 thematic feature words (sorted in descending order by LDA weights)	Paragraph coverage rate	Number of associated policies
Topic 1	Green Management of Express Delivery Packaging	Packaging, courier, eco-friendly, recycling, plastics, biodegradability, circularity, reduction, e-commerce, sleeve	21.3%	11 items
Topic 2	Intelligent Manufacturing and Digital Transformation	Intelligence, Manufacturing, Digitalization, Factories, 5G, Industrial Internet, Equipment, Software, Integration, Solutions	18.7%	13 items
Topic 3	Dual Carbon Goals and Industrial Energy Conservation	Carbon, emissions, energy, energy conservation, carbon neutrality, peak carbon emissions, carbon reduction, clean energy, fossil fuels, industrial parks	17.2%	10 items
Topic 4	Technological Innovation and Standard Development	Technology, Innovation, Standards, R&D, Key Technology Breakthroughs, Platforms, Laboratories, Patents, Research Outcomes, Commercialization	16.8%	14 items
Topic 5	Circular Economy and Resource Utilization	Resources, Circulation, Regeneration, Waste, Comprehensive Utilization, Raw Materials, Renewable, Disposal, Recycling, Landfilling	13.9%	8 items
Topic 6	Institutional Safeguards and Policy Instruments	Regulations, laws, oversight, performance assessment, evaluation, fiscal affairs, taxation, finance, pilot programs, and demonstration projects	12.1%	15 items

The combined coverage rate of the six topics exceeds 100% (as a single paragraph may address multiple topics), yet their individual proportions reflect the distribution of policy attention. Topic 1 (Green Governance of Express Delivery Packaging) leads with a coverage rate of 21.3%, which aligns closely with the intensive rollout of green policies for express delivery packaging in recent years. Topic 6 (Institutional Safeguards and Policy Tools), despite having the lowest coverage rate (12.1%), is associated with the greatest number of policies (15), indicating that institutional safeguards constitute a "penetrative" topic—one that, while not occupying substantial space, is embedded within numerous policy measures.

3.4.3. Inter-theme cross-analysis: Identifying unexplored opportunities in the intersection of "green" and "smart" technologies

To quantify the relationships between various themes, we calculate the probability that any two themes co-occur within the same policy document (i.e., the theme intersection degree). The value ranges from [0,1], where a higher value indicates a greater tendency for the two themes to appear together in the same policy document.

Table 10. Six-Theme Intersection Matrix

	Topic 1: Green Logistics	Topic 2: Intelligent Manufacturing	Topic 3: Dual Carbon Goals and Energy Conservation	Topic 4: Technological Innovation	Topic 5: Circular Economy	Topic 6: Institutional Safeguards
Topic 1	—	0.087	0.234	0.112	0.421	0.198
Topic 2	0.087	—	0.093	0.387	0.056	0.142
Topic 3	0.234	0.093	—	0.178	0.312	0.245
Topic 4	0.112	0.387	0.178	—	0.089	0.291
Topic 5	0.421	0.056	0.312	0.089	—	0.134
Topic 6	0.198	0.142	0.245	0.291	0.134	—

Table 10 reveals several hierarchical patterns of policy theme interrelationships:

Strong topic pairs (cross-degree > 0.30): Topic 1 ↔ Topic 5 (Express delivery green initiatives ↔ Circular economy, 0.421) that Green packaging governance and the circular economy exhibit a high degree of coupling, representing the most mature thematic linkage within the policy framework. Topic 2 ↔ Topic 4 (Smart manufacturing ↔ Technological innovation, 0.387) shows Smart manufacturing policies and technological innovation policies demonstrate strong complementarity. Topic 3 ↔ Topic 5 (Dual carbon goals ↔ Circular economy, 0.312) , The dual carbon goals and circular economy policies form another tight "green triangle."

Weakly correlated pairs (cross-degree <0.10): Topic 1↔Topic 2 (Express Delivery Greenness↔Smart Manufacturing, 0.087); Topic 2↔Topic 3 (Smart Manufacturing↔Dual Carbon Goals, 0.093); Topic 2↔Topic 5 (Smart Manufacturing↔Circular Economy, 0.056); Topic 4↔Topic 5 (Technological Innovation↔Circular Economy, 0.089).

Most notably, the intersection between Topic 1 (Green Governance of Express Delivery Packaging) and Topic 2 (Intelligent Manufacturing and Digital Transformation) was only 0.087, the lowest value among all 15 topic pairs. This indicates that policies addressing green governance of packaging scarcely touch upon intelligent manufacturing, while policies addressing intelligent manufacturing likewise scarcely address green governance of packaging.

3.4.4. Quantification of Cross-Policy Density

We further calculated the number of specific policy documents involved in each pair of topic combinations, quantifying this using the "policy density" metric (number of involved policy documents / total number of 47 policies).

Table 11. Policy density of key theme combinations

Theme Combination	Number of policies involved	Policy density	Appraise
Green Packaging + Intelligent Manufacturing	3 items	0.06	Extremely low
Green Packaging + Circular Economy	16 items	0.34	higher
Smart Manufacturing + Technological	14 items	0.30	higher

Innovation			
Dual Carbon Goals + Circular Economy	11 items	0.23	secondary
Green Packaging + Institutional Safeguards	9 items	0.19	secondary
Smart Manufacturing + Institutional Safeguards	7 items	0.15	secondary

The policy density of "green packaging + intelligent manufacturing" is merely 0.06 among the 47 policies, only three simultaneously address both the themes of "green packaging governance" and "intelligent manufacturing/AI" to varying degrees. This quantitative metric provides rigorous cross-validation of the "dual-centre–weak-link" conclusion derived from the co-occurrence network analysis presented earlier.

3.4.5. Textual Quantitative Summary: The Triple Policy Discourse Structure

Based on comprehensive word frequency analysis, co-occurrence network analysis, and thematic clustering analysis, the discourse landscape of policies related to China's packaging industry can be summarized as a "threefold structure":

The first structural layer: two strong discursive centers, each fully developed.

The "green governance" discourse cluster and the "intelligent/AI" discourse cluster exhibit high internal cohesion (with internal edge densities of 0.743 and 0.681, respectively) and each establishes strong complementary relationships with institutional/standard discourse clusters. In terms of word frequency, both "green" (18.62‰) and "artificial intelligence" (8.15‰) are high-frequency terms, indicating that these two discourse clusters have garnered substantial policy attention in terms of quantitative representation.

The second structural feature: there is a lack of substantive connection between the two discourse centers.

There are only 47 co-occurrence edges between green discourse and intelligent discourse (accounting for 3.8%), with an average edge weight of 1.34; the bridging terms are highly abstract ("enterprise," "manufacturing," "transformation"), while cross-concepts at the operational level are absent. The thematic intersection between "green packaging + intelligent manufacturing" is merely 0.087, and the policy intersection density is only 0.06—indicating that among every 100 relevant policies, only 6 simultaneously address green packaging and intelligent manufacturing.

The third structural layer: the "institutional discourse" that serves an integrative function but does not extend into the "green + intelligent" intersectional domain.

Institutional keywords—such as "standards," "systems," and "evaluation"—exhibit relatively high intermediate centrality, and the discourse clusters of institutions/standards serve as the most critical "bridge" nodes within the network. However, their integrative capacity is predominantly directed toward the "green + institutional" axis (112 edges) and the "intelligent + institutional" axis

(89 edges), yet fails to bridge the disconnect between "green" and "intelligent" domains (47 edges).

These three layers of discourse structure constitute the macro-level context for the subsequent PMC model analysis. If textual quantification delineates the contours of a "two-segmented" configuration at the discourse level, then the question the PMC model seeks to address is: given this separation at the discourse level, what specific structural gaps emerge in operational dimensions such as policy tool design, incentive intensity, and coordination mechanisms?

4. Study Design and PMC Assessment

4.1. Construction of the PMC Evaluation Dimension Framework

Building on the classic framework of Ruiz Estrada (2011) and integrating the policy characteristics of AI-enabled green governance in China's packaging industry, this study constructs a PMC evaluation system comprising nine first-level dimensions (see Table 12).

Table 12. PMC Evaluation Dimension Framework

Primary Dimension	Secondary indicators (each dimension includes 3–5 secondary indicators)	The Relationship Between AI and Green Governance
D1 Policy Nature	Does it include predictive clauses, regulatory clauses, incentive clauses, or guiding clauses?	Clarity of policy orientation
D2 Policy Validity Period	Long-term (>5 years) / Medium-term (3–5 years) / Short-term (<3 years)	Alignment with the pace of technological iteration
D3 Policy Level	Laws / Administrative Regulations / Departmental Rules / Normative Documents	Policy authority and enforceability
D4 Policy Tools	Financial/Tax-oriented / Financial / Standard / Information-oriented / Organization-oriented	The breadth of the policy toolkit
D5 Technical Policy Coverage	AI R&D / Digital Transformation / Intelligent Manufacturing / Data as a Production Factor / 5G + Industrial Internet	Direct level of support for AI enablement
D6 Green Policy Coverage	Carbon emission reduction / Recycling / Green standards / Clean production / Eco-design	Direct support for green governance
D7 AI-Green Compatibility	Does it include AI + green cross-clauses / linkage mechanisms / joint assessments?	Core Dimension: Alignment of the Two Policy Domains
D8 Industry-Specific Focus	Packaging Industry Specialization / Light Industrial Sector / General Manufacturing	Appropriateness of policy granularity
D9 Incentive Intensity	Direct funding / tax incentives / exemplary demonstration projects / standard pilot programs	The driving force of policy on corporate behavior

4.2. PMC Scoring Method

Following the standard procedure proposed by Ruiz Estrada (2011): (1) Each secondary indicator is assigned a binary value of 0–1 (1 if the policy meets the indicator, 0 otherwise); (2) The score for each first-level dimension is the arithmetic mean of the scores of its corresponding secondary indicators; (3) The overall PMC score is the sum of the scores of the nine first-level dimensions, with a maximum possible score of 9; (4) The performance level is categorized as follows: 9–7 points:

"Excellent"; 6.99–5 points: "Good"; 4.99–3 points: "Acceptable"; below 3 points: "Weak".

The ratings were independently completed by three researchers specializing in public policy and the packaging industry. The inter-rater reliability (Krippendorff's Alpha) was 0.83, indicating good consistency among raters. Any disagreements regarding the ratings (out of seven items) were resolved through discussion to reach a consensus.

4.3. Core Policy Examples

Based on the findings of the textual quantitative analysis in Chapter 3, we further screened 17 policies from the 47 policy corpora that were "directly relevant" to AI-enabled green governance in the packaging industry, using them as the core sample for the PMC scoring. The screening criteria were: the policy content must substantially pertain to the packaging industry (or, while not exclusively limited to the packaging sector, must clearly be applicable to it), and must address at least one of the two key domains: "AI/Digitalization" or "Green Governance." The basic information of these 17 core policies is presented in Table 13.

Table 13. 17 Core Policies for the PMC Scoring

Number	Policy Name	Issuing Authority	Year of Publication	Primary associated dimensions
P1	Development Plan for Next-Generation Artificial Intelligence	The State Council	2017①	D5 Technical Policy
P2	"14th Five-Year Plan for Intelligent Manufacturing Development"	Eight departments, including the Ministry of Industry and Information Technology	2021	D5 Technical Policy
P3	Guiding Opinions on Accelerating the Green Development of the Manufacturing Industry	Seven departments, including the Ministry of Industry and Information Technology	2024	D6 Green Policy
P4	Implementation Plan for Achieving Carbon Peaking in the Industrial Sector	The Ministry of Industry and Information Technology and other relevant authorities	2022	D6 Green Policy
P5	Action Plan for Further Advancing the Green Transformation of Express Delivery Packaging	The National Development and Reform Commission and six other departments	2023	D6+D8
P6	Compulsory National Standard: "Requirements on Restricting Excessive Packaging in Express Delivery"	State Administration for Market Regulation	2025	D6+D8
P7	Revised *Provisional Regulations on Express Delivery* (including a dedicated chapter on packaging)	The State Council	2025	D3+D6
P8	"14th Five-Year Plan for Circular Economy Development"	National Development and Reform Commission	2021	D6
P9	"Pilot Project for the Application of Intelligent Manufacturing Standards"	China National Standardization Administration, Ministry of Industry and Information Technology	2025	D5+D8
P10	Action Plan for Digital Transformation of the Manufacturing Sector	The State Council	2024	D5

P11	"Data Factor ×" Three-Year Action Plan	The National Data Administration and other relevant authorities	2024	D5
P12	Guiding Opinions on Accelerating the Establishment and Refinement of a Green, Low-Carbon, and Circular Economic Development System	The State Council	2021	D6
P13	"14th Five-Year Plan for Industrial Green Development"	Ministry of Industry and Information Technology of the People's Republic of China	2021	D6
P14	Guiding Opinions on Promoting High-Quality Development of Light Industry	The Ministry of Industry and Information Technology and other relevant authorities	2022	D8
P15	Digitalization-Driven Action Plan for the "Three-Product" Initiative in the Consumer Goods Industry	The Ministry of Industry and Information Technology and other relevant authorities	2022	D5+D8
P16	Guiding Opinions on Strengthening Industry-Finance Cooperation to Promote Green Industrial Development	The Ministry of Industry and Information Technology and other relevant authorities	2021	D4+D9
P17	Work Plan for the Call for Proposals on Key Tasks for Innovation in the Next-Generation Artificial Intelligence Industry	Ministry of Industry and Information Technology of the People's Republic of China	2018	D5+D9

Note: ① Although P1 was published in 2017, it has still been included in the sample, given its role as a guiding document in the field of AI and its foundational impact on the policy framework from 2018 onward.

5. PMC Analysis Results

5.1. Scores by Dimension

After scoring each of the 17 policies across nine dimensions and calculating the average score, the results are presented in Table 14.

Table 14. Scores by Dimension of PMC (mean scores across 17 policy items)

Dimension	Score	Grade	Standard Deviation	Main Explanation
D1 Policy Nature	0.85	outstanding	0.12	All four functions—prediction, regulation, incentivization, and guidance—are fully covered.
D2 Policy Validity Period	0.72	good	0.18	Medium-term policies dominate (3–5 years), while short-term response mechanisms remain inadequate.
D3 Policy Level	0.78	good	0.15	Departmental regulations and normative documents constitute the primary basis, while legal support remains relatively weak.
D4 Policy Tools	0.65	good	0.19	There is an abundance of standard instruments, but a scarcity of fiscal and tax incentive instruments.
D5 Technical Policy Coverage	0.70	good	0.16	Intelligent manufacturing has broad coverage, whereas AIGC remains a specialized gap.
D6 Green Policy Coverage	0.80	outstanding	0.14	A growing number of binding green governance policies for express delivery packaging have been introduced.
D7 AI-Green Compatibility	0.45	weak	0.22	Core Gap: The two policy domains are operating in near parallelity.
D8 Industry-Specific Focus	0.62	good	0.20	The packaging industry relies heavily on general policies, while specialized policies remain relatively scarce.
D9 Incentive Intensity	0.64	good	0.21	There are numerous exemplary projects, but direct funding and tax incentives remain limited.
PMC Composite	6.41	good	—	Out of a maximum score of 9, it falls at the upper boundary of the "Good"

Score				range.

5.2. Radar Chart Analysis and Dimensional Structure

The nearly circular radar chart comprises nine dimensions: D6 (green policy coverage, 0.80) and D1 (policy nature, 0.85) extend outward, indicating optimal performance. D7 (AI–green policy coordination, 0.45) is severely retracted, forming a distinct "collapse zone"—the only dimension scoring below 0.50. D5 and D6 each achieve relatively high scores (0.70 and 0.80, respectively), yet the "bridge" between them—D7—virtually does not exist. This vividly illustrates two towering peaks—"green policy" and "AI policy"—each standing tall yet remaining disconnected from one another.

5.3. Cross-Validation of Text Metrics and PMC Scores

By systematically comparing the key findings of the textual quantitative analysis in Chapter 3 with the PMC dimension scores in this chapter, we can assess the consistency of the conclusions drawn from the two methodologies (see Table 15).

Table 15. Cross-Validation of Textual Metrics Findings and PMC Scores

Key Findings of Text Quantification	Corresponding to the PMC dimension	PMC score	Consistency Judgment
The "green" discourse strongly dominates the core, with an internal boundary density of 0.743.	D6 Green Policy Coverage	0.80 (Excellent)	✓ High consistency
The "AI/Digitalization" discourse dominates the central axis, with an internal boundary density of 0.681.	D5 Technical Policy Coverage	0.70 (Good)	✓ Essentially consistent
Weak connections between the two centers, with a crossover density of 0.06	D7 AI-Green Compatibility	0.45 (Weak)	✓ High consistency
The institutional discourse exhibits strong integrative capacity but fails to cover interdisciplinary domains.	D4 Policy Tools	0.65 (Good)	✓ Essentially consistent
The packaging industry is prominently featured within green discourse, yet remains relatively marginalized within AI discourse.	D8 Industry-Specific Focus	0.62 (Good)	✓unanimous
Lack of substantive cross-bridging words	D9 Incentive Intensity	0.64 (Good)	✓unanimous

The two methods together establish a complete chain of evidence: text quantification reveals a "dual-center–weak-link" pattern at the discourse level, while the PMC model validates the institutionalized consequences of this pattern at the tool-design level—specifically, the D7 dimension, with a score of 0.45, stands out as the sole "weak" indicator among all dimensions.

5.4. Three structural policy gaps

Through cross-validation using PMC evaluation and text metrics, this study identified three structural gaps:

Gap 1: Discrepancy between AI and green governance policies (D7=0.45)

Among the 17 PMC scoring policies, only one policy (P9 "Smart Manufacturing Standard Application Pilot") simultaneously addresses both "Artificial

Intelligence/Smart Manufacturing" and "Green Manufacturing," with direct regulatory provisions linking the two domains; in all other policies, the provisions concerning these two domains operate in a near parallel fashion. For example, P2 ("Smart Manufacturing Development Plan") elaborates on digitalization and intelligent transformation pathways but does not establish any green constraint indicators; P5 ("Express Delivery Packaging Green Transformation Action Plan") systematically outlines green packaging measures but does not address the enabling role of AI technology. This divergence in policy approaches means that corporate AI initiatives lack institutionalized incentives derived from green governance frameworks, while green practices also lack technical enablement guidance from the AI perspective.

Textual analysis provides a discourse-level explanation for this gap: there are only 47 co-occurrence edges between "green" and "smart," and the bridging terms are all abstract concepts such as "enterprise," "manufacturing," and "transformation," with a notable absence of operational-level cross-terminology.

Gap 2: Lack of specialized incentive tools for AI-enabled green packaging (cross-gap between D4, D5, and D9)

Current policy instruments primarily consist of "standardization-based" measures (e.g.), mandatory national standards restricting excessive packaging, and green certification for express delivery packaging), supplemented by "exemplary demonstration-based" initiatives (e.g.,, smart factory selection programs, and zero-carbon factory cultivation projects). However, dedicated funding mechanisms—such as special funds, R&D subsidies, or tax incentives—directly aimed at enabling enterprises to adopt AI for green packaging remain virtually nonexistent. In the new energy vehicle sector, the "dual-engine" approach combining purchase subsidies and R&D funding has proven effective for technology diffusion; in contrast, a similar combination of policy tools has yet to emerge in the packaging industry. This situation means that enterprises' AI-driven green initiatives remain heavily dependent on internal funding—indeed, the R&D of Great Shengda 's X-FUN platform was entirely self-funded by the company.

Gap 3: Insufficient alignment with industry standards—absence of integration standards for "AI + Green" (cross-gap between D6 and D8)

The packaging industry has already established preliminary green standard frameworks (e.g.), mandatory national standards for green express packaging) and intelligent manufacturing standard frameworks (e.g.,the intelligent manufacturing standard application pilot in which Great Shengda has been selected), yet there remains a lack of integration between these two frameworks. Currently, there are no industry standards or technical specifications specifically addressing "AI-enabled green packaging"—for instance, what technical standards should AI-driven packaging reduction design adhere to? What AI-assisted methodologies should be employed for carbon emission accounting in smart factories? The absence of such

integrated standards means that even when enterprises implement AI+green integration practices, they still lack unified evaluation criteria and a solid foundation for scaling these initiatives.

6. Case Study: Great Shengda and Comparable Companies

The PMC model and text metrics have identified gaps at the policy level; however, how exactly do these gaps influence corporate practices? This chapter employs Great Shengda as the core case study, with Yutong Technology and Hexing Packaging serving as comparative benchmarks, to empirically verify the existence of these gaps and their underlying mechanisms at the micro level.

6.1. Great Shengda: A Pioneering Practice of AI-Enabled Green Governance

Zhejiang Great Shengda Packaging Co., Ltd. (603687. SH) is a leading enterprise in China's paper packaging industry, primarily engaged in corrugated cardboard boxes, cardboard materials, and premium packaging, with total annual revenue of RMB 2.204 billion in 2025. Table 16 outlines its key milestones in the direction of AI-enabled green governance.

Table 16. Key Milestones for Great Shengda 's AI-Enabled Green Governance (2018–2025)

Time	Event	Field of Expertise	Policy Linkage
2018	Launch the construction of an intelligent paper packaging factory	intelligent manufacturing	Aligns with the direction set forth in the "Intelligent Manufacturing Development Plan"
2021	E-pack ET Industrial Internet Platform goes live	Digital Transformation	Consistent with the policy direction of the Industrial Internet
2024	X-FUN Xiaofang AIGC Packaging Platform officially launched (integrating large language models such as DeepSeek and Tongyi Qianwen)	AIGCapply	No direct corresponding policy exists—confirming the D7 gap
May 2025	Selected as a "Zhejiang Province Typical Case of AI-Enabled Manufacturing"	AIapprove	Provincial post-event excellence evaluation (Evidence D9 gap: focus on post-event evaluations, lacking pre-event incentives)
May 2025	Selected for the MIIT's "Intelligent Manufacturing Standard Application Pilot Project" (the sole project in the paper packaging industry)	Guidance by Standards	Corresponds to the P9 policy
September 2025	Selected for the first batch of the "Zhejiang Province Zero-Carbon (Near-Zero-Carbon) Factory" cultivation list (only six factories in the entire province have been selected)	Green Governance	Provincial post-implementation accreditation
October 2025	The XFUN platform has won the Grand Prize in the industry category of the "Cloud Intelligence Computing Cup" AI+ Application Innovation Competition.	Industry benchmark	Technical Approval
2025	The E-pack ET platform has now onboarded over 10,000 enterprises in total.	Platform diffusion	Market validation
2025	Annual revenue reached RMB 2.204 billion, with operating cash flow of RMB 374 million (up 73.09% year-on-year).	Financial Verification	—
2025	R&D expenditure amounted to approximately 82 million yuan (estimated), of which the R&D for the X-FUN platform was fully self-funded by the enterprise.	Self-funded	Gap 2: Absence of dedicated R&D subsidies

Three pathways for AI to empower green governance:

Great Shengda 's practical experience demonstrates the concrete mechanisms through which AI technology drives green governance:

(1) Design Phase – AI-Driven Material Reduction. The X-FUN platform utilizes AIGC to automatically generate packaging design proposals, while AI algorithms optimize material usage, thereby reducing cardboard consumption at the design stage. Traditional packaging design requires 3–5 rounds of sampling and validation; in contrast, AI-driven design compresses this process to just 1–2 rounds, directly reducing paper waste and energy consumption during sampling. This exemplifies the pathway of "AI-driven material reduction → direct carbon reduction."

(2) Production Side – Lean Carbon Reduction in Smart Factories. Smart factories leverage 5G + AI to achieve data-driven operations across the entire production process: AI-based production scheduling optimizes operations to reduce energy consumption from idled equipment; machine vision-based quality inspection lowers defect rates; and predictive maintenance of equipment extends the service life of critical machinery. The combined effect is a significant reduction in energy consumption and carbon emissions per unit of output—this constitutes the technical foundation for Great Shengda 's inclusion in the Zero-Carbon Factory cultivation program.

(3) Full-Chain Approach — Collaborative Carbon Reduction via Industrial Internet. The E-pack ET platform connects over 10,000 upstream and downstream enterprises, enabling order coordination, shared production capacity, and logistics optimization, thereby reducing redundant production and inefficient transportation driven by the "bullwhip effect" across the industrial chain.

Key Observation of Policy Failure:

However, the initiation of the three aforementioned AI+green pathways by Great Shengda has almost entirely stemmed from the enterprises' autonomous decisions. The R&D investment of the X-FUN platform was fully self-funded by the enterprises, and the construction of zero-carbon factories likewise relied on the enterprises' own capital. The role of the policy framework for Great Shengda is manifested primarily as "retroactive recognition"—being selected as a typical case study and receiving commendatory evaluations, rather than as "ex-ante incentives" or "in-process support." This precisely reflects the micro-level underperformance in PMC's analysis, particularly in the scores for D7 (AI-green coordination, 0.45) and D9 (incentive intensity, 0.64). In other words, Great Shengda 's success represents an enterprise's self-driven breakthrough within a policy vacuum, rather than a natural outcome guided by policy interventions.

6.2. Comparative Case Study: Yutong Technology vs. Hexing Packaging

To assess whether the practices of Great Shengda are applicable across the industry, we selected two paper packaging enterprises, either larger or of comparable scale

for a comparative analysis.

Table 17. Comparison of AI-Enabled Green Governance among Three Packaging Enterprises (2025 Data)

Metric	Great Victory	Yutong Technology	Hexing Packaging
stock code	603687.SH	002831.SZ	002228.SZ
Revenue for 2025	2.204 billion yuan	Approximately 17.5 billion yuan	Approximately 12.8 billion yuan
Main business	Corrugated cardboard boxes / cardboard / premium packaging	Premium packaging for consumer electronics and other product categories	Corrugated cardboard packaging
AIGCapply	Developed our proprietary X-FUN platform, setting a new benchmark in the industry.	No publicly available AIGC-specific program	No publicly available AIGC-specific program
Level of intelligence	Ministry of Industry and Information Technology (MIIT) Excellence-Level Intelligent Factory and Intelligent Manufacturing Standard Pilot Project	Jiujiang Yutong Intelligent Factory (production efficiency increased by 30%), AI visual inspection	Construction of digital factories is progressing.
Green Governance	Zero-Carbon Factory Development in Zhejiang Province (6 sites across the province)	Eco-friendly Packaging Industrial Base (investment: 500 million yuan)	Research and Development of Green Packaging Materials
The Integration of AI and Sustainability	High degree of integration (design–production–supply chain)	Each is advancing independently, with no evidence of systemic integration.	Each is advancing independently, with no evidence of systemic integration.
Ways to benefit from the policy	Post-event performance evaluation + standardized pilot program	Local Industrial Investment Policies	Local Industrial Policies
R&D Investment Priorities	AIGC + Green Factory	Smart Manufacturing + Eco-friendly Materials	Digitalization + New Materials

Table 17 reveals a significant phenomenon: even for Yutong Technology (approximately ¥17.5 billion in annual revenue) and Hexing Packaging (approximately ¥12.8 billion in annual revenue)—both of which operate on a larger industrial scale—systematic integration of AI-enabled green governance has yet to be achieved. Yutong Technology is advancing its intelligent and green initiatives along separate trajectories: on one hand, it is implementing intelligent manufacturing projects, such as MES and AI-based visual inspection, at its Jiujiang plant; on the other hand, it is investing ¥500 million to build a high-end eco-friendly packaging industrial base. However, these two efforts lack a cohesive end-to-end system—spanning "AI-driven design to green production"—similar to that of Great Shengda X-FUN. Hexing Packaging faces a similar situation: its digital factory initiatives and green material R&D efforts are progressing in parallel but have yet to converge.

This contrast serves as a counterexample to reinforce the central thesis of this paper: Great Shengda 's integration of AI and green initiatives is not a widespread

phenomenon across the industry, but rather an "advanced exploration" undertaken by a handful of enterprises operating in a policy vacuum. The "fragmented approaches" adopted by Yutong and Hexing precisely reflect the "dual-centers–weak connections" structure of the policy framework at the enterprise level—when existing policies fail to systematically link AI and green governance, most enterprises naturally opt to pursue these two tracks separately, rather than striving for deep integration.

6.3. Overall Conclusions of the Case Validation

By comparing the findings of the case analysis with those from PMC and textometric analyses (see Table 18), the three approaches together constitute a complete evidence chain spanning from the macro to the micro level.

Table 18. Cross-validation of Three-Level Analysis

PMC/Text Metrics Gap	Evidence from the Great Shengda case	Comparative case studies for validation
D7: Lack of AI–green coordination (0.45)	AI-driven green initiatives rely on companies' spontaneous exploration, while policies offer only "retroactive recognition" rather than "proactive guidance."	Yutong and Hexing are pursuing AI and green initiatives in isolation, and existing policies have failed to foster integration between these two domains.
D4/D5/D9: Vacancies for AI Special Incentive Program	The X-FUN platform was developed entirely through self-financing by the enterprise, with no direct funding or tax support.	The lack of incentive among peers to invest in AIGC indirectly reflects insufficient motivation.
D6/D8: Lack of industry convergence standards	Enterprises comply with either the intelligent manufacturing standards or the green factory standards; in the absence of such compliance, no alternative standards may be applied.	An industry-leading AI-powered green packaging standard with no existing benchmarks.

7. Policy Recommendations

Based on the three-fold findings—quantitative evaluation using PMC, textual measurement analysis, and case validation—this paper proposes the following recommendations:

7.1. Establishing an "AI + Green" policy coordination framework

Regarding Gap 1 (D7=0.45; the disconnect between AI and green policies), it is recommended to establish a cross-departmental coordination mechanism titled "AI-Enabled Green Transformation in Manufacturing" at the level of the Ministry of Industry and Information Technology (MIIT). Specific measures include: when revising core documents such as the *Intelligent Manufacturing Development Plan*, add a dedicated chapter on "AI-Enabled Green Manufacturing," specifying that the application of AI technologies must be accompanied by corresponding environmental performance indicators (e.g.energy consumption reduction rate, material utilization rate improvement rate); and when formulating green

manufacturing policies, incorporate dedicated provisions on "Empowerment by AI and Other Next-Generation Information Technologies." The objective is to raise the D7 score from 0.45 to above 0.70—even if full integration of policies across these two domains is not pursued, at least an institutionalized coordination mechanism should be established.

7.2. Establish a specialized fund for AI-enabled green transformation in the packaging industry

To address Gap 2 (insufficiency of fiscal and tax incentive tools), it is recommended that the Department of Consumer Goods Industry of the Ministry of Industry and Information Technology, in coordination with the Ministry of Finance, establish an "AI-Enabled Green Transformation Special Fund" targeting light industrial sectors, including packaging. The fund may cover the following three areas: (1) subsidies for AI-powered green design and R&D (e.g.,, development of AIGC-based reduced-design tools); (2) accelerated depreciation and tax credits for the acquisition of intelligent green equipment; and (3) complementary incentives for the construction of zero-/near-zero carbon intelligent factories. Drawing on the successful experience of the "purchase subsidies + R&D funding" approach in the new energy vehicle sector, the fund should establish a comprehensive policy toolkit comprising "front-end R&D incentives, mid-stage investment credits, and back-end performance-based rewards."

7.3. Accelerate the development of a green packaging standardization framework empowered by AI

Addressing Gap 3 (absence of integration standards), it is recommended that, within the framework of the China Packaging Federation, leveraging the practical experience of pioneering enterprises such as Great Shengda , China first formulate a group standard titled "AI-Enabled Green Packaging Technical Specifications," which, once conditions are ripe, can be elevated to an industry standard and even a national standard. The standard should cover: AI-driven evaluation methods for packaging reduction design, AI-assisted accounting guidelines for carbon emissions in smart factories, and environmental performance assessment indicators for AIGC-based packaging solutions. This approach will transition AI-enabled green packaging from "case-based exploration" to a "standardization track."

7.4. Establish a rapid feedback channel linking "enterprise practices → policy responses"

The case of Great Shengda demonstrates that current policies respond to the practices of cutting-edge enterprises primarily through "ex-post recognition," resulting in a relatively long transmission cycle. It is recommended to establish an "AI + Green Innovation Practice Observation Mechanism" for the packaging industry, thereby systematically integrating the exploratory efforts of leading enterprises into

the policy formulation process. For AI + green technology solutions that have been empirically validated as effective, authorities should expedite their inclusion in recommended catalogs and industry promotion plans, thereby shortening the transmission cycle from "enterprise innovation" to "policy recognition," and ultimately to "industry-wide adoption."

8. Conclusion and Discussion

8.1. Key Findings

Through a mixed-methods design comprising "policy text quantification → PMC model evaluation → corporate case validation," this study systematically identifies three structural policy gaps in AI-enabled green governance within China's packaging industry.

At the macro-discursive level, textometric analysis reveals a "dual-center–weak-linkage" structure in policy discourse: green governance discourse and intelligent/AI discourse have each developed fully (with internal edge densities of 0.743 and 0.681, respectively), yet there is a lack of substantive connections between them, only 47 co-occurrence edges exist, the cross-policy density is merely 0.06, and the bridging lexical items are highly abstract.

At the meso-level, the PMC model quantifies the institutionalized consequences of this landscape: the AI–green coordination dimension (D7) scored only 0.45, making it the sole "weak" indicator among the nine dimensions; the AI-specific incentive tools and industry integration standards also achieved relatively low scores.

At the micro-practical level, case studies of Great Shengda demonstrate that its achievements in integrating AI with green initiatives stem primarily from the company's independent exploration, whereas policy support has largely been limited to "retroactive recognition"; a comparison between Yutong Technology and Hexing Packaging further confirms that the phenomenon of AI and green initiatives operating in silos is the norm rather than the exception within the industry.

The three-tier analysis constructs a progressive chain of evidence, collectively pointing to a core conclusion: China's packaging industry faces a structural "coordination gap" in AI-enabled green governance policies—while both technological policies and green policies function effectively in isolation, there is a lack of an institutional framework to integrate the two. Addressing this gap is crucial for facilitating the transition of the packaging industry from "passive compliance-driven green transformation" to "AI-driven proactive green transformation."

8.2. Methodological Contributions

The novelty of this study lies in the organic integration of policy text quantitative analysis and the PMC index model. Text quantitative analysis provides a macro-level overview of policy discourse ("seeing the forest"), while the PMC model delivers

multidimensional, granular assessments of core policies ("seeing the trees"); together, these approaches establish a progressive analytical pathway from "macro-level patterns → meso-level structures," with both methodologies enabling micro-level validation through corporate case studies. This hybrid methodological design offers a valuable reference for addressing policy gaps in other interdisciplinary domains, such as "AI + green agriculture" and "digitalization + building energy efficiency."

8.3. Limitations and Future Directions

This study has the following limitations: First, the PMC scoring relies on expert judgment; although the scorers demonstrated good inter-rater reliability (α=0.83), it remains difficult to completely eliminate subjectivity; second, the policy text corpus and research sample are limited to the national level, excluding provincial-level and lower-level policies, whereas certain provincial policies (e.g.,The AI-Enabled Manufacturing Case Selection in Zhejiang Province) hold significant operational impact; third, the case enterprises are concentrated within the paper packaging sub-sector, failing to encompass other sub-sectors such as plastic packaging and metal packaging; fourth, the topic labeling in the LDA topic model incorporates elements of the researchers' subjective judgment.

Future research could be extended in the following directions: expanding policy samples to the provincial level to conduct analyses of coordination between central and local governments; broadening the scope of case studies to encompass more specific sub-sectors; and introducing qualitative methods, such as semi-structured interviews, to gain deeper insights into enterprises' subjective perceptions of policy gaps and their corresponding response strategies.

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