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A Study on the Full-Process Functional Design of an Integrated Content Creation Platform for Enterprise Marketing

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ABSTRACT

In the era of digital marketing, corporate content production continues to surge. Traditional offline, fragmented content creation models suffer from inefficiencies in topic selection, difficulty in reusing and accumulating assets, high video production costs, and weak coordination across multiple distribution channels. This paper takes the entire content creation workflow as its research focus, systematically designing core functional modules for five key stages: creative insight, asset management, video production, video editing, and omnichannel distribution. By introducing quantitative modeling methods such as information entropy, cosine similarity, and TOPSIS evaluation models, it transforms experiential business standards into computable metrics, enabling full-process online transformation of content production. Furthermore, the paper analyzes implementation bottlenecks and proposes practical pathways from dimensions including human-machine collaboration, data flow architecture, quantitative evaluation, compliance control, and business closed-loop, providing theoretical and quantitative support for the planning, development, and performance assessment of enterprise-level content creation platforms.

KEYWORDS

Corporate Marketing; Integrated Content Platform; Information Entropy; Cosine Similarity; TOPSIS Model.

1. RESEARCH BACKGROUND

Social media and short-video platforms have become the core channels for corporate brand communication and product marketing. Companies need to continuously produce graphic-text content and short videos, while managing operations across multiple platforms. Traditionally, content creation relies on offline collaboration among planners, copywriters, videographers, and editors. The entire workflow—from trend research and topic ideation to scriptwriting, filming, post-production, and multi-platform distribution—requires manual coordination across various tools. Small and medium-sized enterprises face constraints due to limited human resources budgets, making it difficult to assemble full-fledged content teams. Large and mid-sized companies, meanwhile, manage dozens of new media accounts simultaneously, incurring high labor costs from mass content production. With business processes fragmented and assets scattered across employees' local devices, personnel turnover often leads to loss of valuable content assets. Advances in generative AI and multimodal information processing technologies now provide a technical foundation for transforming content production models. However, most AI-powered creative tools currently available are standalone solutions, addressing only isolated tasks such as text generation or video editing, lacking an integrated system that connects topic selection, asset management, production, distribution, and performance feedback. How to reconstruct the entire offline content

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creation process online, while incorporating quantitative computational models to assess topic quality and content effectiveness, has become an urgent challenge in enterprise digital marketing.

Domestic research on AIGC content production primarily focuses on copyright risks and ethical governance, with only a few studies exploring short video generation technologies. There is a scarcity of applied research that systematically breaks down the entire enterprise content pipeline and integrates quantitative models. While AI writing tools and digital human technologies are rapidly emerging in China's industry, most lack end-to-end closed-loop systems and quantitative evaluation frameworks—this gap forms the research starting point of this paper. Overseas platforms such as Runway and Pika Labs have already launched text-to-video and AI-powered automatic editing features, but their products mainly target individual creators[1-2]. Existing overseas marketing SaaS tools suffer from fragmented functionalities, with data silos across modules like competitor monitoring, script generation, and account distribution. International research tends to emphasize multimodal algorithm optimization, while design studies for enterprise-level, full-process content creation platforms remain relatively underdeveloped.

This paper integrates enterprise content production operations with information entropy, cosine similarity, and the Entropy-Weighted TOPSIS model to establish a quantifiable platform business indicator system, thereby enhancing the theoretical framework for enterprise-level generative AI applications. The study provides comprehensive functional solutions and practical calculation formulas across five modules, supporting platform requirement design and development. The integrated platform facilitates the online transformation of offline operations, reducing human resource costs in content production. Meanwhile, the quantitative model enables objective evaluation of topic quality and dissemination effectiveness, minimizing reliance on subjective experience in decision-making, and thus promoting the implementation of digital marketing strategies across various enterprises.

2. RESEARCH METHODOLOGY

This study integrates business process analysis, literature review, and quantitative modeling methods. By applying business process analysis, it thoroughly maps the actual operational workflow of enterprise new media operations, digitally transforming traditional offline content production processes into five key online functional modules: creative insights, asset management, video creation, video editing, and cross-platform distribution. Through literature review, the study systematically examines academic research and industry policies related to AIGC technology and digital marketing, thereby establishing a solid theoretical foundation for this research.

(1) Topic selection phase: Manual screening of trending topics is inefficient. Manually browsing vast amounts of online information results in a low proportion of effective trending data and a high volume of noise.

(2) Content phase: The copy versions are inconsistent, with a large amount of highly repetitive content. Texts produced by different individuals show high similarity, yet the reuse rate of materials remains low. Text similarity can be measured[3-4] using cosine similarity, whose mathematical expression is shown in Formula (1).

$$\cos(a,b) = \frac{a \cdot b}{\|a\| \times \|b\|} = \frac{\sum_{i=1}^{m} a_i b_i}{\sqrt{\sum_{i=1}^{m} a_i^{\,2}} \cdot \sqrt{\sum_{i=1}^{m} b_i^{\,2}}} \tag{1}$$

Here, a and b represent the standardized vectors of two text segments after vectorization, with values ranging from [0,1]. The closer the value is to 1, the higher the similarity between the two texts, indicating that the platform's content management module can use this formula to identify duplicate or similar materials.

(3) Video production: Real shooting mode involves high time and labor costs, with strong constraints on mass production.

(4) Editing phase: Producing multilingual, multi-version videos results in repetitive work that increases linearly with the number of versions.

(5) Distribution phase: Lacking a unified evaluation system, relying solely on the subjective judgment of operations personnel to assess content quality, with no comprehensive quantitative evaluation metrics.

Traditional models lack quantitative metrics, making business performance highly dependent on practitioners' experience. Therefore, it is necessary to build an integrated platform to digitize operations and introduce mathematical models for objective calculations.

3. CORE FUNCTIONAL MODULES OF THE INTEGRATED CONTENT CREATION PLATFORM

This platform restructures the entire offline enterprise content creation process into an online system, establishing five functional modules: creative insights, asset management, video production, video editing, and full-network distribution. It integrates all business processes, enabling automatic data flow between modules. Additionally, the previously developed quantitative evaluation model is embedded within the platform to automate the calculation and assessment of key performance indicators.

3.1. Creative Insight Module

Creative insights serve as the initial stage of the content creation workflow, encompassing functions such as identifying trending topics, analyzing viral case studies, and monitoring competitor dynamics. The platform leverages publicly available industry data from the internet to build a pool of potential topic candidates, applying information entropy algorithms to quantitatively pre-screen topic value, thereby prioritizing those with higher dissemination potential and providing decision-making support for subsequent content production. The mathematical expression of the information entropy algorithm is shown in Formula[5-6] (2).

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log_2 p(x_i) \tag{2}$$

Here, $p(x_i)$ represents the probability of a particular trending tag appearing; the larger $H(X)$ is, the richer the information contained in the topic, the higher its reference value for topic selection, and the platform can use information entropy to conduct an initial screening of topics.

Hot Topic Selection: Real-time collect public topic data from mainstream new media platforms, analyze topic popularity and tag distribution, calculate the information entropy of each candidate topic—higher entropy indicates richer informational dimensions. Combine with enterprise product keywords for relevance filtering to eliminate social hotspots unrelated to business operations, and output a pool of candidate topics.

The viral content deconstruction module is responsible for structurally dissecting high-traffic viral content across the web, automatically extracting core elements such as title frameworks, narrative logic, and keyword tags. The system identifies frequent characteristics of viral content, builds a database of hit features, and provides reference materials for content planners in topic selection and creation.

The competitor monitoring module continuously collects various content data from competitor accounts, analyzes statistics on topics, posting frequency, and engagement metrics such as likes and

comments, and automatically generates dynamic competitor reports to help businesses stay informed about industry competitors' operational trends in real time.

Through the processes of viral content analysis and competitor monitoring, the platform generates a large number of candidate topics. These are then subjected to an initial quantitative screening using information entropy algorithms to eliminate topics with low dissemination potential. The resulting high-quality topic pool is automatically routed across modules and directly pushed to the downstream asset management module, ensuring seamless and efficient integration throughout the entire business workflow.

3.2. Material Management Module

The material management module receives the topic list output from upstream, integrates copywriting generation, competitor sample references, and AI rewriting functions to produce copy materials, while also establishing a unified enterprise digital asset library. Internally, the module employs cosine similarity formulas to identify duplicate materials.

Based on a topic list and high-quality copy samples obtained through competitor monitoring, the system leverages large language models to generate multiple initial drafts. AI rewriting tools are then used to transform text styles, expand or condense content, adapting it for various scenarios such as short video voiceovers, posts, and e-commerce promotions. All generated copy, images, and scripts are stored in an asset library with relevant business tags. The system employs cosine similarity (as shown in formula (1) above) to compare new content against existing assets; if the similarity exceeds the preset threshold of 0.85, a duplication alert is triggered, notifying operations personnel to take timely action. This helps prevent redundant content in the asset library and significantly improves the efficiency of asset reuse.

3.3. Video Creation Module

The video creation module receives script text from the asset management module and enables batch generation of multimodal video content, featuring three core capabilities: text-to-video generation, AI digital human videos, and image album generation.

(1) Text-to-video generation, which takes script text as input and uses a multimodal generative model to output corresponding video clips, suitable for product scenario demonstrations and industry educational content creation.

(2) AI digital human videos allow users to import a voice-over script and select a digital avatar, then automatically generate an explanation video without the need for live-action filming. This is commonly used for corporate announcements and product feature demonstrations.

(3) Image slideshow generation by uploading image assets and corresponding scripts, transforming static image sequences into dynamic short videos—ideal for product lineup displays, project case promotions, and similar scenarios.

The platform supports batch import of multiple scripts, enabling the simultaneous generation of multiple video drafts. Once created, the video materials are automatically transferred to the video editing module for refined secondary processing. This module effectively addresses the real-world challenges of high production costs and low efficiency in traditional live-action shooting, significantly enhancing the productivity of short video content creation for enterprises.

3.4. Video Editing Module

AI-generated video drafts often suffer from issues such as awkward shot transitions and poor alignment between subtitles and voiceovers. To address this, our platform has developed a dedicated

video editing module that integrates AI-based splicing, multilingual adaptation, and visual editing capabilities. This enables intelligent post-processing of initial drafts, supporting the platform's need for large-scale, high-efficiency video production.

(1) The AI video montage feature can access video clips, audio, images, and other resources from the platform's media library, automatically arranging shots and matching transition effects based on script content, and generating multiple versions of differentiated video materials in bulk, thereby enriching content creation formats.

(2) The multilingual adaptation feature focuses on cross-border marketing scenarios, enabling intelligent voice translation, AI-powered multilingual dubbing, and automatic generation of corresponding subtitles, effectively meeting overseas communication needs.

(3) The module is equipped with a visual editing tool that supports fine-grained timeline editing, allowing staff to manually adjust video clips, subtitle content, and background music, combining the efficiency of AI-driven automation with the precision of manual refinement. Once optimized, the final videos and accompanying copy are automatically pushed to the full-network distribution module, forming a complete content production pipeline.

3.5. Full-Network Distribution Module

The full-network distribution module eliminates the need for redundant content creation, primarily relying on mature copy and video materials generated by upstream processes to carry out promotion and data review. To accommodate the varying specifications across different new media platforms—such as video resolution, title length, body formatting, and cover dimensions—the system automatically reads source materials and standardizes them accordingly. It supports multi-account, batch publishing operations, significantly improving distribution efficiency. After content goes live, the module simultaneously collects cross-channel dissemination data and leverages both entropy weight method and TOPSIS method to fully exploit their respective strengths: the entropy weight method determines the weights of individual indicators, while the TOPSIS method evaluates the ranking of samples in terms of performance. The evaluation results are then fed back into the front-end creative insight module to iteratively refine topic selection and content strategies, forming a complete business loop integrating content production, intelligent distribution, performance assessment, and strategy optimization. The workflow architecture of the entropy weight and TOPSIS methods is shown in Figure 1 [7-8].

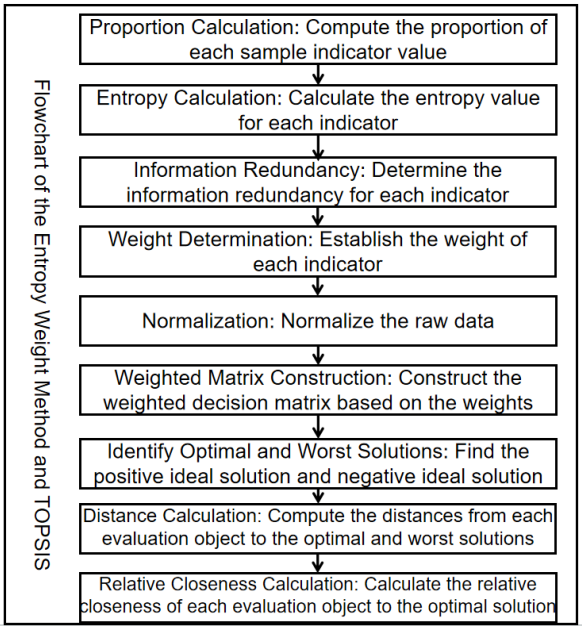


Figure 1. Flowchart of the Entropy Weight Method and TOPSIS

After publication, raw metrics are collected from various channels, including: views, like rate, comment rate, share rate, and lead conversion volume. As shown in Figure 1, the objective weights of each indicator are calculated using the entropy weight method, and then the relative closeness of each piece of content is determined using the TOPSIS model, which yields the comprehensive performance score for that marketing content. A higher score indicates better business effectiveness for that particular topic and content format.

4. PLATFORM FUNCTION OPTIMIZATION AND IMPLEMENTATION PATH

4.1. Human-Machine Collaboration Mechanism

The mathematical models discussed in this article are primarily used for preliminary screening, metric ranking, and decision support throughout the entire content production process. They do not replace human judgment or directly generate final business outcomes, instead establishing a collaborative mechanism of "algorithmic assistance plus human final review." In the creative insight phase, information entropy algorithms quantify and rank topic value, which is then manually verified and confirmed by operations personnel based on industry knowledge, effectively filtering out topics with false popularity. In the asset management phase, cosine similarity is used solely to issue warnings about material duplication, allowing staff to determine whether reuse is appropriate or redundant, thus avoiding blind resource cleanup. During video creation and editing, AI generates initial materials followed by mandatory human review, where editors correct visual flaws and vocal delivery errors to ensure content quality. In the full-network distribution phase, proximity scores generated by the Entropy Weight TOPSIS model serve only as reference rankings for content dissemination effectiveness. Business personnel integrate practical experience into their assessments, preventing overreliance on quantitative metrics when eliminating topics, thereby balancing data objectivity with operational practicality.

4.2. Multi-layered Compliance Risk Control System

The platform has established a comprehensive compliance management system to ensure the standardization and security of content production and distribution. First, it deploys a pre-publication detection engine that screens for prohibited keywords and verifies sensitive content in all text and video materials generated on the platform, thereby preventing compliance risks at the source. Second, it enforces strict copyright control by prioritizing access to image and audio resource libraries with legitimate commercial licenses, while also implementing full-process data authentication for AI-generated content to solidify proof of generation. Third, it clarifies responsibility allocation: the platform explicitly informs enterprise users that AI-generated materials must undergo manual review and verification before public release, placing primary responsibility for content publication on the using enterprises, thus further defining the boundaries of commercial use on the platform.

4.3. Open Customization of Quantitative Metrics for Vertical Industries

The entropy weight-TOPSIS evaluation model adopted in this paper supports customized configuration of industry-specific indicators, enabling it to meet the marketing assessment needs of different types of enterprises with strong versatility and scalability. The platform allows companies to independently adjust their evaluation indicator systems and weight allocations according to their business characteristics: e-commerce enterprises can increase the weights of lead conversion indicators to focus on traffic acquisition and conversion effectiveness; cross-border businesses can emphasize language adaptation and overseas dissemination-related metrics; manufacturing companies can introduce specialized evaluation indicators such as in-depth reading rate. The system supports adding, removing, and fine-tuning indicator weights, precisely aligning with the

differentiated operational requirements across various sub-sectors and enhancing the adaptability and accuracy of content performance evaluation.

4.4. Data Preprocessing

To address issues of online traffic inflation and artificial popularity, data preprocessing is introduced prior to calculating information entropy and TOPSIS, employing the interquartile range (IQR) outlier detection algorithm to filter out abnormal inflated traffic data. First, the lower quartile Q1 is defined as the value at the 25th percentile, and the upper quartile Q3 as the value at the 75th percentile; the IQR is the absolute difference between Q1 and Q3[9]. The mathematical expression for the quartile method is shown in Formula (3).

$$x_o = (x_i < Q_1 - 1.5 \times IQR) \bigcup (x_i > Q_3 + 1.5 \times IQR) \tag{3}$$

5. SUMMARY AND OUTLOOK

In the new media environment, corporate marketing content demand continues to grow, while the inefficiency and poor adaptability of traditional manual content production models have become increasingly evident. This paper addresses enterprise marketing scenarios by designing five core modules for an integrated content creation platform, enabling full digital transformation and online processing of offline content production workflows. The study introduces various quantitative algorithms to optimize operations: using information entropy to evaluate topic value, cosine similarity for duplicate material detection, the entropy-weighted TOPSIS model for quantifying content dissemination effectiveness, and the IQR outlier algorithm for cleaning raw business data. These modules enable seamless data flow and integration, establishing a complete operational loop—covering topic selection, material sourcing, video production, editing, distribution, evaluation, and iterative topic refinement—effectively helping enterprises reduce costs and improve efficiency in content operations. However, multimodal technologies are still in an evolving phase, and quantitative models remain vulnerable to noise interference from network data, making them unable to fully replace human decision-making.

Therefore, the platform is built on the principle of human-machine collaboration, ensuring accurate and effective quantitative evaluation through mechanisms such as compliance risk control systems, industry-specific customizable metrics, and anomaly data filtering. Looking ahead, by leveraging iteratively upgraded multimodal large models, integrating enterprise sales data, and connecting content dissemination with product transaction data, the platform can enhance the TOPSIS evaluation framework to achieve quantifiable assessment of marketing content's commercial value. This integrated platform can serve as a core digital infrastructure for enterprise marketing, significantly improving new media operational capabilities across various industries.

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