
Research on Evolution and Optimization of Social Media Precision Marketing Algorithm Driven by Digital Intelligence

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Abstract: Against the backdrop of deep integration between digitalization and intelligent technologies, social media marketing paradigms are undergoing a fundamental shift from traffic-driven to value-driven approaches. This study focuses on the technical architecture and evolutionary logic of precision marketing algorithms, systematically analyzing the perception mechanisms of multi-source heterogeneous data, the reconstruction pathways of dynamic user profiles, and algorithmic innovations in recommendation systems. The research demonstrates that semantic understanding based on deep learning and association mining through graph neural networks effectively address the data sparsity and cold-start challenges faced by traditional algorithms. The introduction of knowledge graphs enables the transition of user profiles from static labels to cognitive intelligence. Additionally, the study explores the critical role of federated learning in data element circulation to tackle privacy compliance pain points in algorithmic applications. This research aims to provide theoretical support and practical pathways for the intelligent upgrading of social media marketing, fostering a dynamic balance between marketing efficiency and user experience.

Keywords: Digital Intelligence; Social Media; Precision Marketing; Algorithm

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1. Introduction

With the generational leap in mobile internet technology and the widespread adoption of smart devices, social media has transcended its role as a mere interpersonal communication tool, evolving into a core platform that connects users, content, and commercial ecosystems. According to the latest statistics, the global social media user base has surpassed the billion mark, generating massive amounts of user-generated content (UGC) and interaction data that constitute the most valuable production factors in the digital economy era. However, as the traffic dividend fades and information overload intensifies, traditional marketing recommendation algorithms are showing signs of fatigue in terms of accuracy, real-time responsiveness, and user experience, struggling to meet the increasingly complex and diverse user demands. Conventional collaborative filtering and content-based recommendation methods often face limitations due to data sparsity and feature engineering bottlenecks, making it difficult to capture users' deep semantic preferences and latent intentions^[1].

Meanwhile, the technological landscape is undergoing profound transformations. On one hand, breakthroughs in artificial intelligence technologies—such as deep learning, knowledge graphs, and large-scale models—have laid the

groundwork for intelligent marketing algorithms, enabling precise matching from “people seeking products” to “products finding people.” On the other hand, with the implementation of laws like China’s Personal Information Protection Law, data privacy protection has become an indispensable compliance boundary in algorithm design. The core challenge lies in how to leverage advanced algorithmic technologies to uncover users’ deeper intentions and achieve precise marketing resource allocation while safeguarding data security and user privacy. This article systematically explores the evolution and application strategies of social media precision marketing algorithms from four dimensions: data perception, profile construction, algorithm optimization, and privacy compliance, aiming to provide insights for advancing marketing theories and driving technological innovation^[2].

2. Data base of precision marketing: perception and fusion of multi-source heterogeneous data

Data serves as the fuel for algorithmic models, where the breadth, depth, and quality of its collection directly determine the upper limit of marketing precision. In the era of digital intelligence, data collection mechanisms have evolved from single-dimensional static information extraction to dynamic perception across the entire process, involving multimodal and real-time approaches.

2.1. Holographic perception mechanism for multi-source heterogeneous data

Traditional data collection primarily focuses on static user attributes (e.g., gender, age, geographic location) and explicit behaviors (e.g., likes, shares). While explicit behaviors are intuitive, they often suffer from survivorship bias, making it difficult to fully capture users’ psychological profiles. In modern social media environments, data perception mechanisms exhibit multi-source heterogeneity and holistic characteristics^[3].

First, the deep integration of explicit and implicit behaviors has become the norm. Implicit behavioral data—such as user dwell time on pages, swipe speed, mouse trajectories, video playback speed, and bounce points—encompasses richer psychological traits and interest profiles. By quantitatively modeling these implicit feedback signals, algorithms can capture user hesitations, preference levels, and potential churn risks, thereby constructing more comprehensive interest models. For instance, eye-tracking technology or gaze heatmap analysis can precisely identify users’ focus on specific areas of marketing content, providing data-driven support for optimizing ad materials^[4].

Secondly, semantic understanding of multimodal content has emerged as a pivotal breakthrough. Social media content has evolved from single-text formats to rich media forms including images, videos, and live streams. By leveraging Natural Language Processing (NLP) and Computer Vision (CV) technologies, algorithms can perform in-depth content deconstruction. For visual content, the system must not only identify subjects but also analyze compositional aesthetics, emotional tones, and brand identity integration. For video content, temporal sequence analysis is required to examine shot language, narrative pacing, and audio characteristics. This content-based deep semantic analysis transcends the limitations of traditional tagging systems, providing a high-dimensional feature space for precise cross-modal matching.

2.2. Context-aware scenario data

In the mobile internet era, user scenarios are the key to traffic. The spatiotemporal environment users are in is a critical factor influencing their decisions. Data sensing mechanisms must possess contextual awareness capabilities, accurately reconstructing consumption scenarios through sensor data like LBS (Location-Based Services), timestamps, and ambient noise. For instance, during weekday lunch hours in business districts, users’ behavior patterns often exhibit fragmented and function-oriented characteristics. At this time, algorithms should prioritize recommending efficient services such as nearby business quick meals and coffee discounts. Conversely, during weekend home time, users tend to prefer immersive experiences, and algorithms can push long-form video content or home consumption products. By three-dimensionally overlaying user attributes, behavioral preferences, and real-time scenarios, a dynamic mapping relationship of “people-

goods-scenes” can be established, thereby achieving the goal of “delivering the right information to the right person at the right time and place.”

2.3. Data preprocessing and quality governance

After data collection, high-quality preprocessing is essential for ensuring algorithm effectiveness. Social media data often contains significant noise, missing values, and outliers. First, rigorous data cleaning is required to eliminate fake interactions generated by web crawlers and bot accounts, ensuring the authenticity of training samples. The core challenge lies in cross-platform and multi-source identity alignment. Since users employ different IDs across various apps or devices, establishing a unified user identification system is critical. By leveraging probabilistic statistical models and device fingerprinting technology, fragmented IDs can be mapped to unique global user identifiers. This approach bridges social behavior data with transactional data, eliminates data silos, and lays the groundwork for cross-domain recommendation systems.

3. From static labels to dynamic knowledge graph

User profiling serves as the cornerstone of precision marketing, where its quality directly determines the success or failure of marketing strategies. Traditional profiling methods predominantly rely on statistical tags, which fail to uncover latent correlations between attributes and are prone to data sparsity, resulting in ambiguous profiles.

3.1. Vector representation based on embedding technology

Traditional tagging systems struggle to measure subtle user interest differences and calculate similarity between interests. Modern user profiling employs word embeddings and deep learning techniques to map discrete user attributes into low-dimensional dense vectors. This vector representation not only captures explicit features but also captures nonlinear relationships between features through deep neural networks. For example, for users with the same “sports preference,” the vector space model can accurately distinguish between “gear enthusiasts” (focusing on equipment specs) and “event watchers” (following match updates) through cosine similarity calculations. By constructing user interest vector spaces, algorithms can scientifically calculate the match between users and marketing content, significantly enhancing the resolution of user profiles.

3.2. Construction of cognitive intelligence based on knowledge graph

To overcome the limitations of traditional portraits in lacking logical reasoning capabilities, the adoption of knowledge graph technology has become an inevitable choice. By constructing a heterogeneous knowledge graph that includes multiple types of nodes such as users, points of interest, items, and scenarios, the algorithm can leverage the graph structure for semantic reasoning and uncover latent needs^[5].

On one hand, the graph construction enables entity association and attribute inference. When a graph shows a user purchased “infant formula”, the algorithm can leverage the entity relationships (e.g., “infant formula” → “parenting” → “early education services”) to infer potential needs extending beyond the single product category, such as early education courses, family insurance, and large-space vehicles. This graph-based reasoning capability endows marketing recommendations with “cognitive intelligence”.

On the other hand, the structured embedding of social relationships enhances profile accuracy. Social media fundamentally connects interpersonal relationships. By analyzing users’ social network topology and leveraging graph embedding techniques to aggregate feature information from neighboring nodes, algorithms can effectively identify users’ community affiliations. For instance, in fitness-focused social circles, opinion leaders (KOLs) often serve as trendsetters. By quantifying social influence weights, algorithms can differentiate the varying impacts of “strong ties” (close friends,

family) and “weak ties” (like-based connections) on user decisions, enabling precise marketing based on social circles.

3.3. Dynamic image updates and interest forgetting mechanism

User interests are not static but dynamically evolve over time and environmental changes. Traditional static profiling fails to capture this fluidity. Therefore, implementing real-time streaming computing technology to establish a dynamic profiling update mechanism is essential. The system must continuously monitor user behavior streams and incrementally update user feature vectors. Additionally, an “interest forgetting mechanism” should be introduced, applying the Ebbinghaus forgetting curve principle to de-emphasize long-neglected historical interests. For example, if a user frequently browsed maternal and infant products a month ago but recently shifted to cosmetics, the algorithm should automatically reduce the weight of maternal and infant tags while prioritizing cosmetics tags, ensuring recommended content aligns closely with the user’s current psychological state.

4. Intelligent evolution and core applications of precision marketing algorithms

With the advancement of computing power and iterative model architectures, the recommendation system—the core engine of precision marketing—is undergoing a paradigm shift from shallow models to deep neural networks, achieving qualitative leaps in three dimensions: content understanding, collaborative filtering, and content generation.

4.1. Deeply integrated content recommendation algorithm: from feature matching to semantic understanding

Content-centric recommendation algorithms focus on matching content features with user preferences. Traditional methods rely on manual extraction of keywords or TF-IDF weights, which often fail to capture deeper semantic information.

In feature extraction, deep semantic representation technology has replaced traditional keyword matching. For text content, pre-trained language models (e.g., BERT, GPT series) can leverage self-attention mechanisms to deeply understand textual context, metaphors, and emotional tendencies, capturing long-tail keywords and latent themes. For image and video content, algorithms combining Convolutional Neural Networks (CNN) and Transformer architectures extract spatiotemporal features, interpret visual language and narrative pacing, thereby recommending content that aligns with user aesthetic preferences. For instance, when processing a landscape image, the algorithm not only identifies elements like “mountains” and “water” but also detects aesthetic preferences such as “minimalist style” or “film texture,” matching users with similar aesthetic tastes.

At the model matching level, the application of deep interest networks addresses the challenge of user interest drift. The algorithm no longer treats historical user behavior as a static set, but instead introduces an attention mechanism to dynamically calculate the weight of historical behaviors based on current candidate content. For example, when browsing sports shoes, the user’s purchase record from six months ago may carry lower weight, while yesterday’s browsing history carries extremely high weight. If the user has long followed tech review bloggers, the algorithm will assign higher attention weight to related content. This dynamic modeling approach effectively captures the evolution of user interests, enhancing the timeliness of recommendations^[6].

4.2. Deep integration of graph neural networks and collaborative filtering

As a cornerstone of recommendation systems, collaborative filtering algorithms have long been constrained by data sparsity and cold start issues. The introduction of Graph Neural Networks (GNNs) has revitalized collaborative filtering, enabling it to process high-dimensional sparse data and uncover deep-seated correlations. This statement is error-free.

Traditional collaborative filtering can only capture second-order interaction relationships and struggles with higher-order connectivity. Social media user behaviors exhibit complex graph structure characteristics. By employing Graph Convolutional Networks (GCNs) or Graph Attention Networks (GATs), the algorithm facilitates information transfer

and aggregation on user-item bipartite graphs. Through multi-layer GCN propagation, the algorithm identifies latent similarities between user A and user B—where user A has no direct interaction but is connected through multiple social network tiers. This graph-based higher-order collaborative filtering effectively uncovers deeper collaborative signals, significantly improving recall rates.

Moreover, recommendation mechanisms that enhance social trust have become increasingly sophisticated. In social media, user decisions are profoundly influenced by trust relationships. Graph neural network-based social recommendation models integrate social relationship graphs with interaction behavior graphs. The algorithm employs an attention mechanism to learn the influence weights of friends on user decisions, distinguishing between the varying impacts of “strong ties” and “weak ties.” For instance, in recommending maternal and infant products, the algorithm assigns higher weight to behaviors of friends within the user’s social circle who have parenting experience, thereby boosting the recommendation’s credibility and conversion rate.

4.3. Multi-task learning and Multi-objective optimization

In real-world marketing scenarios, platforms prioritize not only click-through rate (CTR) but also conversion rate (CVR) and user retention. Traditional single-objective models often fail to balance these metrics effectively. Modern recommendation systems widely adopt multi-task learning architectures like ESMM (Entire Space Multi-Task Model), which share underlying feature representations while optimizing both click-through and conversion goals. Through joint training, these models address sample selection bias by leveraging click-space sample data to assist in conversion-space parameter estimation, thereby maximizing marketing conversion effectiveness while ensuring user experience.

4.4. AIGC-driven intelligent generation of marketing content

Since 2024, the surge of generative artificial intelligence (AIGC) has revolutionized the marketing content supply chain, transforming the industry from “content recommendation” to “customized creation”. Leveraging large language models (LLMs) and diffusion models, platforms now automatically generate marketing copy and visual assets tailored to user profiles. For cost-conscious audiences, algorithms produce data-driven copy emphasizing discounts and product comparisons, while emotional marketing focuses on storytelling-driven content with emotional resonance. This personalized content generation has significantly boosted click-through rates (CTR) and conversion rates. By integrating computer graphics and speech synthesis technologies, AIGC can create virtual digital anchors for 24/7 immersive interactive marketing, dramatically enhancing engagement and efficiency.

5. Algorithmic compliance and challenges from the perspective of privacy computing

While precision marketing strives for maximum effectiveness, data privacy and security have become an unbreachable red line. Traditional data silos and primitive data transmission models are no longer sustainable, and privacy-preserving computing technology has emerged as the key to resolving this dilemma.

5.1. Compliance path to break data silos

In the social media marketing ecosystem, data is often fragmented across multiple platforms and advertisers, creating ‘data silos.’ For instance, platforms hold users’ social behavior data, while brands possess transactional data. Federated learning, as a distributed machine learning framework, operates on the principle that ‘data remains within the domain and remains invisible.’

In practical implementation, federated learning typically follows these steps: First, participants (platforms and advertisers) train models locally using private data. Second, they securely upload encrypted model gradients or parameters to a centralized server. Third, the server performs secure aggregation to update the global model. Finally, the updated model is distributed to all parties. Throughout this process, raw data never leaves the local environment, with only

encrypted model parameters being exchanged. This approach not only bridges data silos and enables data value circulation, but also strictly complies with legal requirements for localized data storage and privacy protection, making it the standard technology for implementing precision marketing algorithms in the future.

5.2. Differential privacy and Full-link protection

In the data collection and model training phases, differential privacy technology is implemented by introducing carefully designed noise into query results or model parameters, preventing attackers from inferring sensitive information about specific individuals through output results. Meanwhile, homomorphic encryption technology ensures data remains encrypted throughout transmission and computation, rendering it unanalyzable even if intercepted. This end-to-end data security framework provides robust safeguards for the compliant operation of precision marketing algorithms.

5.3. Algorithmic ethics and the governance of “Information Cocoon”

While precision marketing algorithms enhance efficiency, they have also sparked ethical debates such as “information cocoons” and “big data price discrimination”. When algorithms overfit users’ historical preferences, they may lead to homogenized recommendations and narrow users’ perspectives. Future algorithm design should incorporate fairness and diversity mechanisms, mandating a certain proportion of exploratory content in recommendation strategies to break users’ interest loops. Simultaneously, establishing algorithm transparency mechanisms to explain recommendation rationale, granting users the right to disable personalized recommendations or modify profile tags, will help achieve a balance between technological rationality and humanistic care.

6. Conclusion

In the digital intelligence era, social media’s precision marketing algorithms are undergoing a profound technological revolution. From multi-source heterogeneous data integration and quality governance, to dynamic profile mapping, deep learning evolution and AIGC empowerment, and finally privacy-preserving computing security, the entire marketing ecosystem is evolving toward smarter, more efficient, and compliant solutions. Future precision marketing algorithms will no longer be cold traffic harvesting tools, but intelligent assistants with deep understanding, creative generation capabilities, and privacy protection. Social media platforms and marketers must stay at the forefront of technology, striking the optimal balance between algorithmic efficiency, user experience, and ethical compliance to drive the healthy and sustainable development of the digital marketing industry.

Disclosure statement

The author declares no conflict of interest.

References

- [1] Yang LME, 2026, The Impact of Social Media Marketing on Consumers’ Online Purchase Intention: Mediated by Emotional Resonance and Brand Trust. *Journal of Business Economics*, (02): 76-79.
- [2] Luo HJ, 2025, Exploring the Path of Precision Marketing in Social Media Big Data Empowered by AI. *International Public Relations*, (21): 140-142.
- [3] Zhao ZY, 2025, User Behavior Analysis and Precision Marketing Strategies in Social Media E-commerce. *Modernization of Shopping Malls*, (15): 62-64.
- [4] Yang Y, Niu CY, 2024, Research on Precision Marketing Strategies Based on Social Media. *Brand Marketing of Time-*

honored Brands, (16): 18-20.

- [5] Liu JJ, Liu B, 2024, Analysis of the Dissemination Effect of Digital Media Technology on Social Media Platforms. *Satellite TV and Broadband Multimedia*, 21(14): 4-6.
- [6] Feng LQ, 2024, A Media Company's Overseas Social Media Content Marketing Strategy Research, University of Electronic Science and Technology of China.

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