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How to Improve Marketing Efficiency and Precision through AI-Driven Innovative Products

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Abstract: The rapid emergence of big data and artificial intelligence has significantly transformed the marketing paradigms of traditional enterprises, offering unprecedented opportunities for growth and structural evolution. This article systematically summarizes critical technological advancements, including data-driven marketing strategies, the construction of sophisticated user behavior models, and the integration of natural language processing for enhanced market insights. It further explores the fundamental design concepts of intelligent marketing systems and the practical implementation of these systems within corporate environments. By examining marketing methodologies from multiple strategic perspectives, this study proposes actionable frameworks to achieve data-driven precision marketing and highly refined customer management. Furthermore, the paper provide strategic suggestions for enterprises seeking to establish a robust and scalable intelligent marketing framework. Through the integration of automated analytics and predictive modeling, these approaches aim to optimize resource allocation and improve consumer engagement, ultimately providing a comprehensive technical and theoretical roadmap for digital transformation in the modern commercial landscape.

Keywords: artificial intelligence; intelligent marketing; customer profile; natural language processing; marketing automation

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1. Introduction

With the advent of the Internet era, enterprise marketing is undergoing a profound transformation from mass marketing to precision marketing. In particular, the development and progress of a series of technologies represented by artificial intelligence, whether it is the management of big data, the establishment of models, or the understanding and application of natural language, have all become important transformative technological forces in marketing development. They have enhanced enterprises' ability to understand customers and also changed customers' behaviors in the market, altering marketing activities themselves [1]. This article mainly focuses on exploring the technical paths of AI in marketing, aiming to enhance the marketing effectiveness and accuracy of enterprises through innovative products to facilitate their intelligent growth.

2. The Key Technical Basis and Theoretical Support of Artificial Intelligence in Enterprise Marketing

2.1. Technical Principles of the Integration of Data-Driven Marketing and AI

Traditional marketing methods draw factors based on individual experience and overall market analysis, and fail to track consumers' preferences and behavioral changes in a timely manner. The data-driven sales approach based on a large amount of data has conducted in-depth consumer information analysis using artificial intelligence technology, achieving precise and timely sales plans. The core idea is based on generating a predictive model to transform past behaviors into probability estimates of future responses.

At the technical application level, logistic regression is a supervised learning algorithm often used to model market responses, suitable for solving problems between two categories, such as "whether to click on the advertisement" or "whether to make a purchase". Its mathematical model is as follows:

$$P(y=1|x)=\frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_n x_n)}} \tag{1}$$

Among them, $x_1, x_2, \ldots, x_n$ represents the user characteristic variables, such as browsing time, click frequency, interest tags, etc., β_0 is the bias term, and $\beta_1, \beta_2, \ldots, \beta_n$ is the corresponding feature weight. This model can generate consumers' behavioral tendencies towards a specific marketing activity, providing decision-making references for the implementation of strategies such as advertising placement, email sending and one-on-one advice by enterprises. Based on the real-time information interaction and dynamic model correction functions, enterprises can build a closed-loop dynamic feedback mechanism, continuously correct the model parameters, gradually improve its prediction accuracy, and ultimately achieve the enterprise marketing goal of cost reduction and efficiency improvement [2].

2.2. Algorithm Framework in Customer Behavior Modeling

Customer behavior is the most fundamental starting point of precision marketing. By applying the customer activity model, it is possible to predict the activities that customers will undertake in the subsequent period of time, such as whether they will continue to use, whether they will become paying users, and when they will leave, etc., thereby enabling the implementation of customized and precise marketing plans. The commonly used methods for depicting the change sequence of customer activities are sequence modeling and reinforcement learning.

Markov Decision Process (MDP) is widely used in dynamic behavior prediction, especially in the modeling of multi-stage and multi-decision customer path problems. Its mathematical formula is as follows:

$$V(s)=\max_{a}\left[R(s,a)+\gamma\sum_{s'}P(s'|s,a)V(s')\right] \tag{2}$$

The $V(s)$ in the formula represents the maximum expected benefit that can be obtained after taking the optimal behavior in a certain state s. $R(s,a)$ is the immediate reward obtained by performing action a in state s; γ is the discount factor, representing the present value weight of future earnings; And $P(s'|s,a)$ is the probability of transitioning from the current state s to the next state s' through behavior a.

At the application level, state s refers to the current behavior of the user (such as viewing products, purchasing products, checking out, etc.), and behavior a refers to the marketing strategy (such as distributing coupons, warning users, showing personalization). By establishing and optimizing different strategic paths, enterprises can carry out resource allocation and user incentives that maximize efficiency [3].

2.3. Natural Language Processing Methods in Marketing Interaction

Current marketing interactions are not merely achieved through images and structured buttons; they are more often carried out through natural language, such as intelligent customer service, conversational bots, user review analysis, and email generation. This trend embeds natural language processing (NLP) technology into the marketing process. Adopting artificial intelligence to understand and generate users' language can enhance the ability of emotion recognition, intention recognition and interaction response time, thereby improving the consumer experience and conversion efficiency.

For the underlying layer, NLP is a lexic-based vector representation technology, which converts discrete text representations into operable vectors in a continuous space.

Among them, Skip-gram is a representative vocabulary embedding model. It predicts the possibility of the occurrence of a certain word in the context based on the current word, and its training objective function can be defined as:

$$J = \sum_{t=1}^{T} \sum_{-c \le j \le c, j \ne o} log\, P\left(w_{t+j} | w_t\right) \tag{3}$$

Among them, w_t is the current word, w_{t+j} is the word in its context, and the window size is c. The trained model can understand the semantic relationships between words, enabling words with the same semantics to match in the vector space to enhance the machine's understanding of semantics.

In actual business promotion, enterprises use lexical embedding to construct the comment meaning space of products, perceive the emotions of commenters, or apply generative algorithms to automatically generate advertising and feedback texts. With the help of the Transformer structure, this model can solve the problem of long documents, grasp the relevant background of long documents, and has more advantages in building detailed and precise interaction tools to achieve precise marketing [4].

3. AI-Driven Innovative Product Architecture and Key Technology Realization

3.1. Overall Architecture and Module Design of the Intelligent Marketing System

The AI-based intelligent marketing system covers data flow, processing flow and decision-making flow, and realizes the intelligence and automation of the process. The process is organized around the customer, mainly including data collection, characterization, modeling, information production, strategy formulation, reactivity adjustment and other processes [5].

Data from various sources enter the system through interfaces, including customer networks, apps, SNS, and various activities, preferences, and consumption data within the CRM system. Data processing cleans, normalizes and extracts features from the raw data to form a data structure that can be modeled. Then, based on the principles of deep learning and graphic models, multi-level attributes of customers are established. Finally, through behavior prediction models (LSTM, Transformer), the behaviors that customers may have in various scenarios are extracted and constructed.

The content generation module will generate advertising copy, push content, suggested phrases, etc. based on the user's preferred tags and marketing promotion strategies by using NLP technology, thereby ensuring that the advertising information can precisely target the needs of the target consumer group. The marketing strategy decision-maker determines the best materials, channels and time, etc. by using optimization algorithms based on the user's response probability, business opportunity cost, the number of tweet posts, etc.

After the online placement platform is installed, it will continuously obtain user feedback information such as click-through rate, conversion rate, and dwell time. Then, through the model feedback stage, the data will be trained and updated to form a data closed loop, thereby enhancing the applicability and effectiveness of predictive decisions. The overall process is shown in Figure 1 as follows:

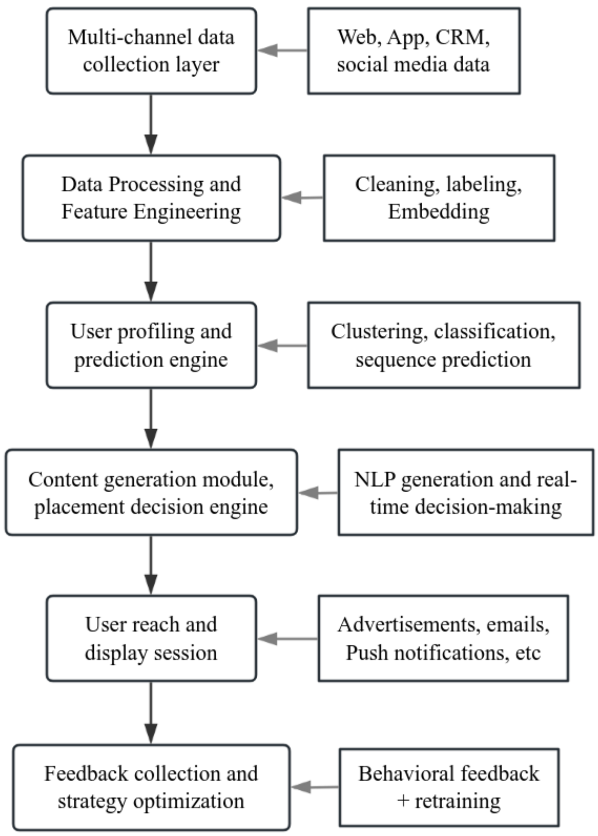

Figure 1. Flowchart of the overall architecture of the intelligent marketing system.

The architecture not only achieves a high level of technical integration capability and business flexibility, but also can leverage a modular design layout model to adapt to different enterprise marketing and operation scenarios, achieving intelligent and data closed-loop growth.

3.2. Core Algorithm Techniques for User Profile Construction and Behavior Prediction

The core of user portrait modeling is feature engineering and unsupervised models. Data from different channels (such as purchase records, browsing trajectories, terminal hardware, social attributes, and other identifiable user data, etc.) are structured after being unified through methods such as One-hot encoding, Embedding vectors, and TF-IDF. Distinguish the static labels (such as gender, region, terminal device, etc.) and dynamic labels (such as interest preference, activity level, purchase process, etc.) in the portrait labels. Generate labels for discrete annotation through classification methods such as K-means, and also establish a topological structure through graph embedding to obtain node characteristics. For cases where social relationships are relatively close, GNN models such as GraphSAGE or GCN can be adopted to enhance the ability to depict user interest profiles.

For action prediction, the most common technical approach is deep sequence construction. A typical architecture is a time pattern model composed of LSTM, which converts user behaviors into vectors and sequences them into the model in chronological order, and acquires long-term correlations through the time sliding window method. The most common input sequences include action types, timestamps, and background characteristics, etc. Finally, the click or conversion results are estimated through the fully connected network combined with the Sigmoid function:

$$h_t = \mathrm{LSTM}(x_t, h_{t-1}); \hat{y}_t = \sigma(W h_t + b) \quad (4)$$

In addition, the Attention mechanism enhances the model's attention ability to key action points, and the Transformer is utilized to strengthen the parallel capability and the ability to model long sequences. The model is trained using the gradient descent method of the cross-entropy loss function. Finally, the model is deployed as an online prediction model and combined with the user behavior log and the recall model to obtain a prediction model with higher accuracy and greater rationality.

3.3. Technical Implementation of AI-Driven Content Generation and Advertising Placement System

Produce content based on pre-trained language models and adopt deployment modes such as the Encoder-Decoder structure (such as T5) and the Decoder-only structure (such as GPT). First, generate multiple candidate contents through search or filtering, and then transfer this information to the text generation model to modify and reshape these contents. The input information includes background information such as the product name, audience preference identification, and sales season, and organizes it into the Prompt template. For example, "Create a marketing copy for camping equipment in May for men who love outdoor activities." Setting Top-k sampling or Top-p sampling in the generation stage is conducive to controlling the diversity of generation and avoiding overly standardized answers.

At the model deployment layer, in the inference stage, ONNXRuntime/TensorRT acceleration is combined and used. Combined with keyword control or Style Embedding technology, specified styles such as different styles of specification type, sales type and emotion type are generated in real time. The generated copy was screened for the best version through multiple rounds of tests by the reviewers and CTR, and the effect of going online was verified by cold start A/B testing.

The strategy engine is the core of advertising bidding. It can take into account user behavior characteristics and feature information (such as current time, frequency, region, etc.), and make placement decisions based on strategy rules and model ratings at the same time. The strategy engine adopts the reinforcement mode (such as DQN or PPO) for training through the simulation environment, aiming for the highest total return. The placement process is embedded in the RTB system, sending bid requests to the DSP in real time, receiving exposure and click action data feedback, and achieving strategy optimization by comparing the effects of different strategy versions. The bandit algorithm is adopted to automatically correct the importance of the strategy, and the intelligent strategy of automatic allocation is realized.

4. The Key path of AI Technology in Enhancing Marketing Efficiency and Accuracy

4.1. Intelligent Customer Segmentation and Personalized Strategy Optimization Path

As part of the customized strategy placement in the intelligent marketing system, customer segmentation is crucial in this stage. The marketing intelligent system starts with obtaining consumers' visit, purchase records, and personality attribute characteristics. Through feature engineering, it conducts data standardization, encoding, embedded vectoring and other processing. PCA or automatic decoders are used to reduce the dimension and compression of the processed data, maintaining the features of the main behavioral patterns and reducing the sparsity of high dimensions to facilitate subsequent merging.

The processed data mentioned above will be input into the classification algorithm for the classification of the crowd. For urgent screening requirements, K-Means is more suitable, while for the fine analysis of complex data patterns, GMM or DBSCAN is advisable. Each cluster is a user group with similar behavioral characteristics. The system will perform policy mapping based on the pre-set content, form, contact frequency, contact mode, etc. of the policy rule template. For instance, high-quality content recommendations are made for highly active individuals, while reminder messages are sent to customers for less active ones. When the strategy is implemented, the system feeds back the corresponding behaviors of users under the strategy in real time to determine the response of the strategy, and adjusts the importance of the strategy or updates the classification model for the continuous optimization of the audience - placement - feedback link (see Figure 2).

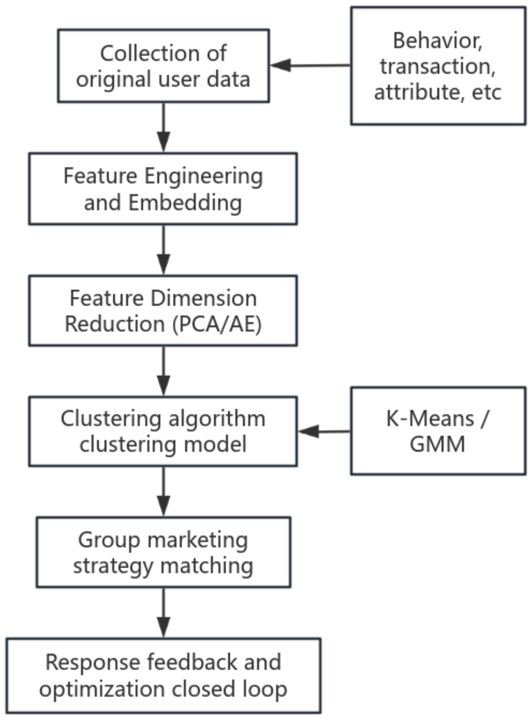

Figure 2. Flowchart of Intelligent Customer Segmentation and Personalized Strategy Optimization.

This method establishes a closed loop, covering the construction of data models, the issuance of strategies and the adjustment of result feedback. Through the openness of the algorithm and the ability to receive data in real time, intelligent and precise marketing for a wide range of dynamic user groups can be achieved.

4.2. Ways to Enhance Marketing Automation and Process Intelligence Assisted by AI

The goal of marketing process automation is to automatically transform the previously complex marketing processes into a system that can be configured and executed. AI plays three roles: automatic content delivery, time cycle matching, and dynamic distribution channel strategies.

In terms of content expression, it proposes diverse information touchpoint schemes based on users' personal attributes and real-time behavior flows, and finds the "optimal touchpoint" through a sequential model. For example, a user is browsing a product but has not made a purchase yet. Within the next 72 hours, the preferred touchpoints are email touchpoints + Apppush touchpoints, and the preferred type of touchpoint messages is the "time-limited discount" type. These decisions are driven by the strategy model + rule system, and the optimal combination is selected from the rule database in a dynamic weighted manner.

Time scheduling refers to the dynamic adjustment of the placement time through historical response behavior data and multi-arm slot machine algorithms. The system analyzes the behavioral interaction probabilities of different types of users in various time periods to calculate the optimal placement window and achieve rhythm control based on behavioral habits.

Channel strategy iteration is carried out through real-time multi-channel A/B testing. Users are divided into different groups under preset standards. The system continuously observes the content feedback on each platform. The obtained information is fed back to the placement strategy engine to achieve dynamic iteration and cyclic learning, and the algorithm model is updated regularly to maintain the optimal response path of the system.

Furthermore, the low-code automated orchestration platform enables marketers to generate strategy deployments without programming when promoting. Subsequently, the scheduler drives the execution of various API and algorithm services in the application, thereby achieving a continuous cycle of "planning - execution - feedback".

4.3. Strategy Feedback and Intelligent Iteration Mechanism in Data Closed-loop Analysis

The data closed loop is an information tracking and dynamic regulation mechanism based on the three-level feedback mechanism of "perception - evaluation - optimization", so as to accurately grasp and regulate the implementation status of each marketing. Generally speaking, a data closed loop usually involves three aspects of work, namely behavior observation, model evaluation, and strategy regeneration. Among them, the behavioral observation stage is to continuously track all data and information related to user responses, covering the entire journey trajectory from advertising placement to sales, such as clicks, exits, browses and conversions, etc. The model evaluation stage is to measure the effects of all strategy groups, such as CVR, CTR, ROI and ΔCLV, etc. The final result will directly drive the strategy engine to automatically adjust or initiate the retraining process of the model layer based on its triggering frequency (such as trigger frequency, file type, file bit) (see Table 1).

Table 1. Key Indicators and Optimization Paths in Closed-loop Systems.

Indicator type	Description	Data source	Optimization means
CTR	Click-through rate, a measure of the attractiveness of content	Advertising/Push log	Modify the title, image and sending time
CVR	Conversion rate, a measure of conversion ability	Page + order data	Optimize the landing page and recommendation algorithm
ROI	The input-output ratio measures the return on investment	Advertising budget and revenue	Adjust the bidding strategy and refine user filtering
User LTV increment	Life cycle value changes	CRM+ Transaction Records	Strategy retention, activation, and enhancement of sticky content delivery
Strategy coverage rate	The proportion of effective strategies hitting the target users	Grouping + Reach records	Improve the segmentation accuracy and optimize the channel matching logic

The above-mentioned various indicators will reach their peaks and then regressed as the system conducts real-time monitoring, triggering the adjustment of algorithms and the recombination of marketing strategies. This can truly achieve data iteration-driven development and enhance the intelligence and adaptability of the entire marketing system.

5. Conclusion

The current enterprise marketing business driven by AI encompasses the entire application process, including enterprise data collection, marketing strategy application, and reverse feedback of marketing processes. Innovative products based on AI achieve intelligence from process to content and then to decision-making. This article mainly introduces technical theories, system architectures and key technical algorithms, and explores how to use intelligent marketing systems to assist enterprises in improving marketing efficiency and accuracy. It can be foreseen that in the near future, based on the continuous improvement of model capabilities and data quality, AI will demonstrate more powerful predictive, interactive and flexible capabilities for enterprise marketing, becoming an inexhaustible driving force for the continuous development and growth of enterprises.

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