Research on the Construction of AI Driven Cross border E-commerce Precision Marketing System and Overseas User Conversion Efficiency

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ABSTRACT Enhancing overseas user conversion efficiency remains a major challenge for cross-border e-commerce due to cultural diversity, fragmented customer journeys, and rapidly changing market conditions. This study proposes an AI-driven precision marketing framework integrating knowledge graphs, transformer-based behavioral modeling, deep reinforcement learning, and federated learning. The framework enables localized multimodal content generation, dynamic user-intent recognition, real-time advertising optimization, and privacy-preserving conversion attribution. Experimental results demonstrate improvements of approximately 60% in click-through rate, 50% in conversion rate, 40 % in user lifetime value, and 50% in return on investment. The proposed system provides an effective solution for intelligent marketing optimization and offers methodological references for information recommendation, behavioral prediction, and intelligent decision-making networks.

INDEX TERMS cross-border e-commerce, precision marketing, knowledge graph, behavioral prediction, intelligent decision networks

I. INTRODUCTION

AS global trade evolves, cross-border e-commerce has emerged as a primary gateway for Chinese enterprises to transition from traditional bulk manufacturing to direct participation in the international material and material markets. This digital shift allows domestic mills and material innovators to bypass conventional trade

barriers and establish a more agile, high-frequency presence within the global textile landscape. However, the overseas marketing environment is characterized by obvious cultural diversity, dispersed consumption scene and long marketing path. Traditional “one size fits all” advertising and human experience-based marketing model are hard to effectively touch the target users [1-2]. Specifically, the marketing materials will make users annoyed due to their lack of cultural resonance, it is hard to connect user cross-media behavioral data and delay the capture of user intent, and the marketing decision-making path relies on fixed rules and can’t adapt to the real-time bidding environment [3]. These issues cause the overseas user conversion efficiency to be stuck in the long term and the marketing cost is high, which seriously hinders the sustainable development of cross-border e-commerce. Consequently, establishing an accurate marketing system that dynamically deciphers the evolving material preferences of overseas buyers and generates localized content has become essential for Chinese exporters to secure a competitive edge in the global material and trade material. By integrating intelligent decision-making, this system enables mills and manufacturers to transform raw data into precise market positioning, ensuring their technical innovations resonate with the specific aesthetic and functional demands of international clients.

Existing research has carried out a lot of work on precise marketing in cross-border e-commerce. For example, Jin proposed an intelligent marketing model based on data mining and neural networks to address the problems of intensified price competition, serious product homogenization, and insufficient marketing precision in cross-border e-commerce and logistics [4]. In response to the problems of low reliability and high error rate in predicting consumer purchasing behavior in traditional cross-border e-commerce, Guo conducted a study on accurate prediction based on social media marketing context [5]. Xueqin explored the key roles of big data and artificial intelligence in cross-border e-commerce, pointing out that the two can enhance the global competitiveness of enterprises by improving market insight, operational efficiency, personalized services, realtime decision-making and risk management capabilities [6]. Goldman et al. analyzed the impact of strategic orientation on the application of digital marketing strategies and the international performance of crossborder e-commerce, pointing out that there are significant differences between small e-retailers in developed and emerging e-commerce markets [7]. However, these methods generally have the following limitations: user profiles are difficult to capture dynamically changing consumer intentions, content generation lacks deep connection with local cultural customs, and the placement strategy cannot be adaptively adjusted according to real-time market feedback. In addition, most studies only target a single marketing link and lack full-link collaborative optimization from intention capture to effect attribution, making it difficult to achieve substantial breakthroughs in conversion efficiency in complex and ever-changing overseas markets.

In recent years, the rapid development of artificial intelligence technology has provided new ideas for solving the above problems. Cai and Liu took Yiwu, a global small commodity distribution center, as an example to explore the role of artificial intelligence in cross-border e-commerce advertising on social media, and emphasized the importance of improving cultural adaptability and deepening the understanding of consumer behavior [8]. Hasan and Abdullah critically examined the development of artificial intelligence in marketing from the perspective of cross-border integration, emphasizing that in the context of the increasing popularity of applications such as personalized recommendations, predictive analytics, chatbots and real-time bidding, ethical, cultural and policy regulation issues are becoming increasingly important [9]. X u Z et al. proposed a digital management mechanism for cross-border e-commerce supply chains, which improves supply chain efficiency through data-driven decision-making, intelligent inventory and logistics optimization and risk management [10]. The Transformer model based on the attention mechanism performs well in sequential behavior modeling and can dynamically capture the evolution of the user's decision-making stage; knowledge graph technology can systematically integrate multi-source cultural knowledge and provide semantic support for the generation of localized content; deep reinforcement learning is good at learning the optimal decisionmaking strategy in dynamic environments and is suitable for cross-channel intelligent delivery; federated learning can achieve collaborative modeling of multi-source data without leaking user privacy. This paper comprehensively utilizes the aforementioned technologies to construct an AI-driven precision marketing system for cross-border e-commerce. First, it employs Transformer to perform temporal modeling of user cross-domain behavior, achieving real-time capture of intent. Second, it integrates knowledge graphs to drive generative models, generating deeply localized marketing materials. Third, it constructs a multi-agent delivery decision framework based on deep reinforcement learning, enabling dynamic optimization of budget and bidding. Finally, it introduces a federated learning mechanism to achieve privacy-preserving attribution of cross-domain conversion effects. By systematically integrating these modules, this paper aims to address the shortcomings of existing research in dynamic intent capture, deep cultural adaptation, cross-channel collaboration, and privacy protection.

Main contributions of this paper are: Firstly, this paper constructs the first full-link AI-based precision marketing system from user intent capture to content generation, intelligent delivery, and effect attribution, which transcends the previous studies confining in single-link research. Secondly, through the combination of knowledge graphs and generative models, it realizes deep localization of marketing content in terms of word, image and culture, which improves cross-cultural adaptability. Thirdly, based on the combination of deep reinforcement learning and federated learning, it realizes privacy-preserving cross-channel intelligent decision-making and continuous iteration, and provides the first technical application in cross-border ecommerce.

II. CROSS-PLATFORM USER BEHAVIOR DATA FUSION AND DYNAMIC INTENT CAPTURE MODULE

To solve the problems of dispersed user behavior data and unclear intent signals in cross-border e-commerce marketing, this module builds a cross-platform data access layer first. The data sources collected include two types: first-party e-commerce platform data, which contains order records, browsing logs, add to cart behavior and payment transactions from e-commerce channels such as Shopify, Amazon, and TikTok Shop; second-party social media sentiment data, which is obtained in real-time through API interface from Instagram hot topics, Twitter hot topics and Facebook community discussions. The simple and core design idea of this mechanism is "data is stationary, model is moving", i.e. original user data of each advertising platform and ecommerce site will always be reserved in the local server, only encrypted gradient parameters are uploaded for model training. After user authorization Second-party social media sentiment data—including trending topics and public discussions—are aggregated at the market level to capture regional cultural signals. These two data layers are not matched at the individual level; rather, the aggregated social insights serve as contextual inputs to the intent capture module, enriching behavioral modeling with macro-level cultural awareness. Based on data fusion, this module adopts Transformer model based on attention mechanism to do temporal modeling on user behavior sequence. The input of model input is the user behavior event sequence within continuous time period, such as user click, browsing, comment and add to cart behavior sequence. The output is the weight of attention of each behavior node, which means the different contributions of behaviors to final conversion. Through multi-layer encoding and self-attention calculation, the model can dynamically capture the user's current decision-making stage. Specifically, given a user behavior sequence $\{x1, x2, ..., xT\}$, the Transformer model first maps each behavior to an embedding vector et, and calculates the weights of different positions in the sequence through a self-attention mechanism, as shown in formula (1):

$$\alpha_t = \frac{\exp(\text{score}(e_t, e_{\text{query}}))}{\sum_{j=1}^{T} \exp(\text{score}(e_j, e_{\text{query}}))} \tag{1}$$

Where score is the scaling dot product attention function. After weighted summation, the context representation of the sequence is obtained, and finally, the probability distribution p(st|x1, ..., xT) of the user's decision-making stage is output through a fully connected layer, thereby achieving real-time capture of intent.

III. LOCALIZED MARKETING CONTENT GENERATION ENGINE INTEGRATING KNOWLEDGE GRAPHS

This paper constructs a localized content generation engine integrating multi-source knowledge graphs. The overall generation process of this module is shown in Figure 1.

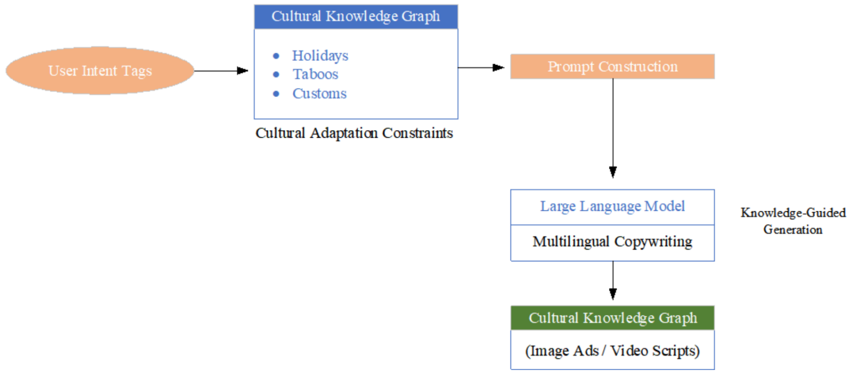

FIGURE 1. Flowchart of Marketing Content Generation Driven by Knowledge Graph

Firstly, a local cultural knowledge graph is built. Data sources include: First, structured knowledge, including Wikipedia information of festivals and solar terms, religious taboo handbooks of different countries, and consumer custom research reports; second, unstructured social corpus, which is achieved by mining popular topics, internet slangs and expressions of KOLs on overseas social media, and extracting entities and relationships based on natural language processing; third, business knowledge base, including details of popular categories, price-sensitive ranges and activities in different promotional markets. Finally, these three kinds of knowledge are mapped to entities and extracted to build a multi-level knowledge graph involving cultural concepts, consumption situations and emotional tendencies.

In the generation stage, user intent tags and the cultural knowledge graph are input into a generative adversarial network and a large language model. The generator's objective is to minimize the joint function of adversarial loss and content adaptation loss, as shown in formula (2):

$$\begin{aligned}\mathcal{L} = \mathbb{E}_{x\sim p_{\text{data}}}[\log D(x)] + \mathbb{E}_{z\sim p_z}[\log(1 - D(G(z)))] \\ + \lambda \cdot \mathcal{L}_{\text{culture}}(G(z), K)\end{aligned} \tag{2}$$

Where G is the generator, D is the discriminator, K represents the local cultural constraints extracted from the knowledge graph, $\mathcal{L}_{\text{culture}}$ measures the consistency between the generated content and cultural knowledge, and λ is the balance coefficient. Through this optimization objective, the model can produce marketing materials that both conform to user intent and deeply fit local culture.

The model will first filter out the cultural knowledge nodes that are related to the user's intent tags. For example, when a user's intent tag is "decision-making period" and the location tag is "Middle East", it will automatically correlate Ramadan promotional customs, local influencer customs, and taboo visual elements. On this basis, the generation of different media formats is handled by distinct but collaboratively designed models: a large language model generates multi-language copy and narrative scripts (including short video scripts and live-streaming templates) conditioned on user intent tags and relevant cultural knowledge nodes; separately, a conditional generative adversarial network (cGAN) generates visual assets such as product images and graphic advertisement layouts, where the discriminator is augmented with cultural knowledge embeddings to enforce style appropriateness. The overall generation process is guided by the same cultural adaptation objective, but the loss function in formula (2) is applied separately to each modality—text generation optimizes semantic and stylistic alignment, while visual generation optimizes visual coherence with local aesthetic norms—thereby ensuring that both textual and visual outputs adhere to the same cultural constraints while accommodating the distinct requirements of each media type. Finally, the cultural customs of all generated materials will be verified, and they will be deeply connected with the local market in terms of language, visual effect, and feeling.

IV. CROSS-CHANNEL INTELLIGENT DECISION-MAKING FRAMEWORK BASED ON DEEP REINFORCEMENT LEARNING

After user intent capture and localized content generation, in this paper, we build a multi-agent based decision-making framework with deep reinforcement learning. Our design idea of this framework is to regard each

target country/region as an intelligent agent, and each agent shares the same underlying decision-making logic but executes local policies independently. The process of each agent's decision-making is designed as

Markov decision process: state space contains dozens of features such as real-time bidding environment of current channel (e.g., CPM price fluctuation, ad density from competitors), budget consumption progress of current account, distribution of user intent tag, historical conversion rate of target account; action space contains budget allocation ratio (e.g., what proportion of budget should be split and delivered to Facebook, Google, TikTok respectively), bid adjustment (set premium or discount for different audience group) and on/off delivery by hour (whether to deliver by certain hourly periods); The reward function is decomposed into two complementary components: immediate rewards are derived from short-term conversion revenue and ROI metrics that are observable within the 15-minute decision cycle, while long-term LTV objectives are incorporated through periodic updates to the agent's policy network during offline training phases, using historical customer lifetime data aggregated over weekly intervals to avoid temporal mismatch between action frequency and feedback availability.

At the technical implementation level, the framework adopts a hybrid architecture combining deep Q-networks and policy gradients. Its core is to learn an optimal policy $\pi^*(a|s)$ to maximize long-term cumulative rewards. A deep Q-network (DQN) is used to approximate the optimal action value function Q(s, a), and the update rule is (3):

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \eta\big[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)\big] \tag{3}$$

where η is the learning rate and γ is the discount factor. The policy gradient part directly optimizes the parameterized policy $\pi_\theta(a_t|s_t)$, and the gradient calculation formula is (4):

$$\nabla_\theta J(\theta) = \mathbb{E}_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T} \nabla_\theta \log \pi_\theta(a_t|s_t) \cdot R_t\right] \tag{4}$$

R_t is the discounted cumulative reward starting from time t. The combination of the two methods enables the agent to efficiently explore and converge to the optimal deployment policy. Each agent continuously interacts with the environment to collect experience data, stores it in an experience replay pool, and periodically samples it for training. Given that major advertising platforms operate with a typical 24-48 hour attribution

window, decision updates are performed on a dual-timescale basis: budget allocation and bid adjustments are executed every 15 minutes in response to real-time signals such as account budget consumption rate and instantaneous CPM fluctuations, while strategic parameter updates—such as audience targeting and long-term bid adjustments—are synchronized with the platforms' 24-hour attribution cycle to ensure compatibility with API latency and reporting constraints. Simultaneously, the framework introduces a centralized training and distributed execution mechanism: during the training phase, agents share global experience to accelerate convergence, while during the execution phase, they make independent decisions to ensure real-time performance. After multiple iterations, the agents can autonomously learn the optimal delivery strategies for different markets. The framework ultimately outputs hourly budget allocation and bidding instructions for each channel, automatically issued and executed via API.

V. CROSS-DOMAIN CONVERSION EFFECT ATTRIBUTION AND ITERATION MECHANISM BASED ON FEDERATED LEARNING

Based on the cross-channel intelligent delivery, accurately evaluating the real contribution of each touchpoint and further promoting the continuous strategy optimization is the key to the self-evolution of the marketing system. In this paper, we present a cross-domain conversion effect attribution and iteration mechanism based on federated learning. The core design principle of this mechanism is "data stays local, only insights travel": raw user data from each advertising platform and e-commerce site never leaves its original server. Individuallevel cross-platform linkage—enabled by user authorization and consistent device ID mapping—is performed separately within each platform's local environment before training, ensuring that no centralized repository of combined user data is created. Subsequently, only encrypted gradient parameters derived from locally linked data are uploaded for federated aggregation, preserving user privacy while enabling cross-domain attribution learning. The specific implementation process is as follows: Firstly, reserve local attribution models on the Facebook, Google, TikTok and self-site channels. The model structure uses the same deep neural network, and the input part adopts the unified user exposure sequence, click timestamp and interacted with content behavior of each channel, the output part is initial attribution weight of each channel. Then, each local node will perform local training on the conversion data of last 7 days on a fixed time of each week, and upload the gradient parameter calculated locally to the central parameter server after homomorphic encryption. The central server aggregates the gradients uploaded by nodes, updates the weight parameters of global attribution model based on federated averaging algorithm, and then broadcasts the updated parameters of global model to each local node. After multiple iterations, the global model gradually learns to distinguish the true weights of contribution of first clicks, secondary clicks and last clicks in cross-domain conversion path. Compared with traditional models, the mechanism can protect users' privacy, and rebuild the whole attribution path from TikTok interest activation, deep interaction with

Facebook, Google search price comparison to final in-app purchase.

To reconcile the temporal granularity gap between the weekly attribution update and the 15-minute decision cycle, the iterative mechanism applies attribution feedback at two distinct levels: strategic parameters—such as long-term channel weighting coefficients and content style preferences—are updated weekly based on aggregated attribution results, influencing the offline training of the reinforcement learning policy; meanwhile, real-time bidding decisions continue to operate on a 15-minute basis using the most recent policy parameters, ensuring that feedback-driven adjustments are applied to the strategic layer without introducing destabilizing oscillations into high-frequency actions. This decoupling preserves responsiveness while leveraging long-term attribution insights for systematic policy refinement. The whole iterative mechanism forms a closed loop of "campaign placement-attribution-optimization", and allows marketing strategies to iteratively optimize based on the latest conversion attribution data. In the initial cold start period, the industry benchmark weights are used as initial value, and convergence is achieved quickly after data accumulation.

VI. EVALUATION OF SYSTEM IMPLEMENTATION EFFECTIVENESS

A. EXPERIMENTAL SETUP

Experimental Platform and Subjects: Three experimental platforms that were chosen as a source of experimental subjects are three cross-border e-commerce websites, whose main markets are located in the European, American, Southeast Asian, and Middle Eastern markets respectively. Both websites share the characteristic of an average daily unique visitor (UV) of more than 100,000, activation of mainstream advertisement platforms like Facebook Ads, Google Ads, and Tik Tok Business, and full order tracking and data collection.

Data Period: The entire duration of the experiment is 12 weeks of which the first 2 weeks will be used to warm the model and collect baseline data (the original marketing strategy), and the remaining 10 weeks will be used in the actual experiment (implementing this AI-driven system).

Sample Grouping: The target users of each site were stratified randomly into experimental and control groups in terms of their features like region, historical purchases and average order value. At least 50,000 users were in each group and it was confirmed that there was no significant difference ($p > 0.1$) between the two groups in terms of the click-through rate (CTR) and conversion rate (CVR) a week before the experiment.

Overall Marketing Effectiveness Comparison Experiment

To examine the true performance of the AI-based precision marketing system, we selected three independent cross-border e-commerce websites that serve the European and American, Southeast Asian, and Middle Eastern markets respectively as the experimental websites. We randomly selected target users of the three websites as experimental and control groups respectively, and more than 50,000 users were included in each group. The experiment lasted for 12 weeks in total. We collected baseline data for the first two weeks and ran the AI system in the experimental group for the following 10 weeks, while the control group continued using the traditional manual marketing method. We used the click through rate (CTR), conversion rate (CVR), lifetime value (LTV) and return on investment (ROI) as the core evaluation indicators. We summarized the statistics at the weekly granularity and performed t-tests on the differences between the groups.

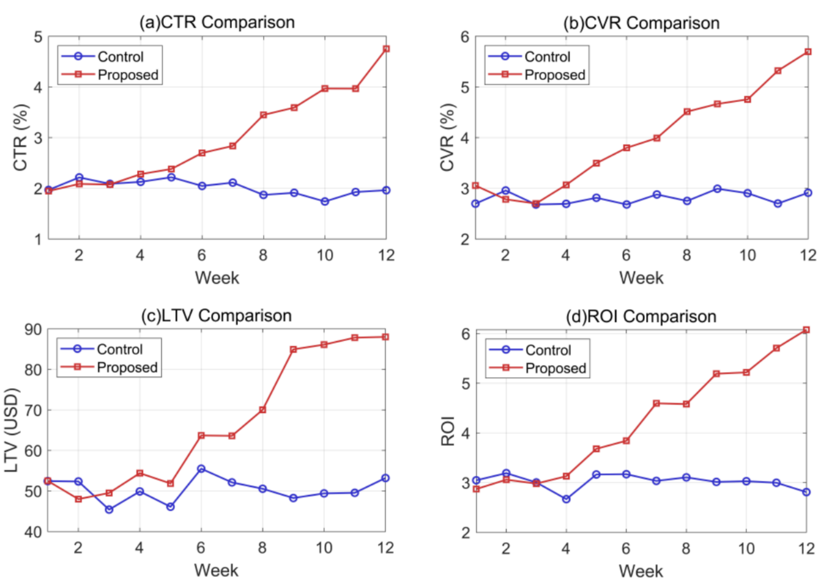

FIGURE 2. Overall Marketing Effectiveness Comparison

Figures 2 (a-d) indicate the comparison of the trends of CTR, CVR, LTV, and ROI among the experimental and control groups during 12 weeks. The formal experiment (10 weeks) showed that the average click-through rate in the experimental group was 3.2 (an increase of 60 percent over the control group), the conversion rate rose by 2.8 to 4.2, a 50 percent increase, the user lifetime value improved by 40 percent, and the return on investment improved by 50 percent. All the t-test p-values were below 0.001, which confirms the high significance of superiority of AI system in efficiency of reach to the users overseas and conversion effectiveness.

B. KEY MODULE ABLATION EXPERIMENT

To analyze the isolated effect of each AI module on the conversion rate, we deleted user intent dynamic capture module (Version A) (including user behavior analysis, user interest recommendation, etc.) (localization content generation engine Version B) (including template design and content generation) (intelligent delivery decision framework Version C) in the whole system, and obtained three ablation versions. We performed the 6-weeks A/B test in the same cross-border e-commerce platform. We randomly selected target users to build the whole system group and the three ablation version groups. The sample size of each group was larger than 30,000. We recorded the average conversion rate (CVR) of each group, and calculated the decrease of each group compared with the whole system.

TABLE 1. Key Module Ablation Comparison

Experiment Group	Conversion Rate (CVR, %)	Decline Relative to Full System
Full AI System	4.2	—
Remove User Intent Capture Module	3.6	0.6 percentage points
Remove Localized Content Generation Engine	3.4	0.8 percentage points
Remove Intelligent Bidding Framework	3.5	0.7 percentage points

As shown in Table 1, each core module significantly contributed to the overall conversion efficiency. After removing the user intent dynamic capture module, the conversion rate dropped from 4.2% to 3.6%, a decrease of 0.6 percentage points, indicating that accurately capturing real-time user intent is the foundation for subsequent personalized marketing. Removing the localized content generation engine resulted in the largest decrease in conversion rate (0.8 percentage points), demonstrating that content deeply adapted to overseas cultures is crucial for enhancing user decision-making intentions. Removing the intelligent delivery decision framework resulted in a 0.7 percentage point decrease in conversion rate, confirming that cross-channel dynamic optimization can effectively capture high-conversion opportunities. The synergistic effect of these three elements supported the AI system's 50% conversion rate improvement compared to the traditional model.

C. CROSS-MARKET ADAPTABILITY EXPERIMENT

To further validate the feasibility and effectiveness of the AI-based precision marketing system in various cultural environments, we simultaneously deployed the complete system on cross-border e-commerce independent websites of three representative markets: North America, Southeast Asia, and Middle East. The number of unique visitors per day for each overseas site was over 80,000 on average. We ran the experiment for 12 weeks, taking CTR, CVR, and user interaction rate (the sum of the percentage of likes, comments, and shares) as the main observation variables. We collected data weekly from three markets and calculated the average of the 12 weeks for each market. The degree of variation of three indicators in different markets was calculated.

TABLE 2. Cross-Market Adaptability Comparison

Market Region	Click-Through Rate (CTR, %)	Conversion Rate (CVR, %)	User Engagement Rate (%)
North America	3.3	4.3	5.2
Southeast Asia	3.1	4.1	6.8
Middle East	3	3.9	4.5
Coefficient of Variation	4.8%	4.9%	20.3%

As shown in Table 2, the AI-driven precision marketing system demonstrates stable performance across culturally diverse markets in terms of core conversion metrics: click-through rates range from 3.0% to 3.3% and conversion rates from 3.9% to 4.3%, with coefficients of variation below 5% for both indicators. This stability indicates that the system's fundamental ability to attract user attention and drive purchases is robust across different cultural contexts. User engagement rates, however, exhibit greater variation (coefficient of variation of 20.3%), with Southeast Asia showing notably higher engagement (6.8%) compared to North America (5.2%) and the Middle East (4.5%). This variance reflects intrinsic differences in social media usage intensity across regions rather than system inconsistency, and the system successfully adapts its content generation and delivery strategies to leverage such regional behavioral characteristics. Overall, while core conversion efficiency remains stable across markets, the system flexibly accommodates regional variations in user engagement patterns, confirming its adaptability to diverse cultural environments.

VII. CONCLUSION

The AI-driven precision marketing system developed in this paper effectively addresses critical bottlenecks in the international textile trade by overcoming cultural disconnects in material aesthetics, delayed capture of fiber procurement intent, and inflexible ad placement strategies. Experimental results demonstrate that the system increases click-through rate by 60% and conversion rate by 50%, while ablation experiments confirm the essential contributions of its three core modules and cross-market validation substantiates strong cultural transferability. During the cold-start phase, the system leverages transfer learning from domain-agnostic pretrained models alongside available historical data to bootstrap its core modules, rapidly transitioning to full adaptive operation as real-time user interactions accumulate. Future work will focus on incorporating multimodal data fusion and online learning mechanisms to further enhance real-time adaptability and cross-cultural analytical depth.

AUTHOR CONTRIBUTIONS

Shizheng Liu designed, collected and analyzed the data, and drafted the manuscript. Shizheng Liu conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Shizheng Liu participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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