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The Application of Artificial Intelligence in Personalized Marketing

Yuyang Yin *

Alliance Manchester Business School, Manchester University, Manchester, United Kingdom

* **Corresponding author**: (Email: 1472366323@qq.com)

Abstract: With the all-around development of digital marketing and personalised advertising, artificial intelligence technology has now begun to change the structure of the marketing system to a certain extent. Systematically present the technical struc ture (data layer and algorithm layer) and basic application scenarios of AI in personalised marketing in this paper, such as user profiling and segmentation, personalised recommendation systems, intelligent pricing and promotion, and automated content production. Research has shown that AI can improve the conversion rate and increase the efficiency of user operation, but there are still problems such as a lack of transparency in algorithms, privacy risks, information cocoons, and a weakening of brand culture; in the future, efforts will be made to promote the sustainable and responsible development of personalised marketing by coordinating technological innovation with ethical governance.

Keywords: Artificial Intelligence, Personalized Marketing, User Profile.

1. Introduction

With the all-round development of the digital economy, methods of marketing have changed again and again, gradually shifting from "mass marketing" to "precision marketing", and now, "personalised marketing" has also begun to appear. The old way of advertising and recommendation is no longer ideal, so now people want these systems to be more personalized based on their individual traits and circumstances. Personalisation of marketing has appeared, aiming to present users with personalised content and goods in an appropriate time and place via different paths. However, the old rule-based marketing system cannot respond to changes and various needs of different users well; therefore, more intelligent and adaptive technology is needed urgently[1][2].

In recent years, many achievements have been made in the application of artificial intelligence technology for personalised marketing. In the past, many researchers have studied user behaviour, refined recommendation algorithms and improved prices, etc. These studies have shown that AI can be applied to enhance the conversion rate and user retention of the system. Although the preceding studies have achieved some results in improving technological efficiency, other deficiencies still exist; among them are issues such as ethical dimensions of technology, user experience, system explainability, etc[3-5].

Systematically study the technical structure, main application scenarios and economic value of artificial intelligence in personalised marketing in this paper, and focus on analyzing the implementation process in user profiling, recommendation systems, intelligent pricing and automated content generation. At the same time, this paper also elaborates on the main problems of the current AI marketing system, such as algorithm transparency, fairness risks, privacy protection and human-computer collaboration, and looks forward to the future development direction of multimodal data integration, edge computing and human-computer collaboration.

2. Technical Framework of AI in Personalized Marketing

In the technological architecture of personalised marketing, artificial intelligence has advanced through the stages of perception and decision-making, and has now reached the level of creation. At the bottom of this structure are the data and algorithm levels.

The Data Layer is the Foundation of the Whole System. The company will obtain various kinds of data and no longer need to use only one type. These are users' online activities, such as clicks and browsing records. Emotional expressions on social media, a user's shift in location, and other physiological signals are also included. Through the integration of space-time and multiple senses, build a dynamic and highly digital user profile for the enterprise.

Some algorithms are used to improve marketing results more precisely at the algorithm level. Collaborative filtering, matrix factorization and neural networks are typical examples of traditional machine learning and deep learning algorithms used to find hidden patterns in large amounts of data. These algorithms can help the system move from "people looking for goods" to "goods being selected by people" and provide personalised recommendations.

Natural Language Processing Technology can be applied to marketing systems to enable conversation between users and the system. It can sense the current emotion of the user, respond to changes in their feelings promptly through a chatbot, and provide customised materials based on those emotions.

Computer Vision Technology Expands Marketing Applications Offline. Facial recognition technology will be employed by the company to recognise members' faces for shopping. It can also recognize changes in a person's face in real time to switch different modes for offline stores.

Generative Artificial Intelligence has brought the system to the stage of automatic content generation. Now it is not necessary to spread the original materials; instead, personalised posters and animated videos can be generated in real time based on the individual attributes of each user, and artificial data can also be fabricated in certain situations. This way will be personalised marketing for all the people.

A closed-loop architecture for multi-modal data input and multiple algorithms has been designed to improve the accuracy of the personalised marketing system. At the same time, the system can also adapt to different environments dynamically, create content independently, and thus establish a high technological barrier in commercial competition.

3. Core Application Scenarios of AI in Personalized Marketing

3.1. User Profile and Segmentation: Construction of Dynamic Label System

Zhang et al. conducted research on user churn warning and precise propagation strategies in the wireless communication industry. This study breaks through the limitations of traditional user tags being static and isolated, and proposes a multi algorithm collaborative modeling method that integrates K-Means clustering, association rules, and decision trees [6]. The key innovation lies in not only automatically identifying heterogeneity in user behavior patterns through cluster analysis (such as distinguishing high-value stable users from high-value low value users with high churn risk), but also systematically integrating multidimensional behavior characteristics (such as call records, traffic usage, application preferences, geographic location) with churn warning mechanisms. This upgrades the model from "describing the current state of the user" to "predicting the future behavior trajectory of the user". The research team validated the user profile driven propagation strategy through A/B testing. The results indicate that personalized push and incentive measures based on user profiles significantly improve user conversion rates and retention levels. Compared to traditional unified marketing methods, this approach significantly improves the matching degree between content and users. This case fully demonstrates the value of multi-source data fusion in enhancing predictive capabilities. Relying solely on a single indicator such as consumption amount is difficult to accurately capture the risk of loss. However, by incorporating heterogeneous information such as geographic location and application preferences, the model can identify more complex precursor signals of loss. At the same time, this method has been validated in real business scenarios of communication operators, indicating that the complete process from data cleaning, feature engineering to model deployment has practical operability.

However, there are certain limitations to the research. On the one hand, constructing such a detailed user profile requires collecting a large amount of sensitive information such as personal location. On the other hand, although research has mentioned that user behavior has dynamic evolution patterns, in practical engineering, if real-time or near real-time label updates cannot be achieved (such as using stream processing frameworks), the prediction accuracy of the model will decrease over time.

3.2. Personalized Recommendation System: Real time Distribution of Streaming Media Content

The Kwai technical team uses the EMER framework to make self evolving multi-objective ranking recommendations. Traditional recommendation systems generally use manually set weighting formulas to sort content, which pre assign weights to indicators such as likes and viewing time, and then calculate the comprehensive score. This approach essentially scores each content independently, ignoring the core logic of "comparison and selection" in recommendation scenarios.

The End to End Multi objective Fusion Retraining (EMER) framework proposed by Kwai has achieved breakthroughs in two aspects: first, let models compare each other among the same batch of candidates, rather than scoring in isolation, so as to make better ranking decisions; Secondly, a new optimization metric called "Unit Time Interaction Probability" is proposed to replace the traditional "Single Content Interaction Probability", significantly improving the consistency between offline training and online performance [7].

On the main app, the EMER framework increased seven day retention by 0.133%, dwell time by 1.199%, and single stream short video views by 2.996%. In the high-speed version, the seven day retention increased by 0.196% and the dwell time increased by 1.392%. Although the absolute increase is not significant, for super applications with hundreds of millions of daily active users, this is equivalent to bringing retention improvements and considerable economic benefits to millions of users [7].

This solution solves a long-standing problem in recommendation systems - good offline evaluation results but poor online performance. EMER has successfully improved the consistency between offline and online by redefining optimization objectives. At the same time, it achieves an automatic balance between multiple objectives such as improving retention and increasing viewing time, avoiding the blindness of manual parameter tuning in traditional methods. However, due to the highly opaque decision-making process of end-to-end deep learning models. When there is a deviation in the recommendation results (such as user fatigue caused by excessive promotion of qualitative content), it is difficult for the team to quickly locate the root cause of the problem. Secondly, the computational cost of this framework is much higher than traditional methods, with extremely high requirements for real-time inference latency and server computing power, making it difficult for small and medium-sized platforms to replicate.

In addition, KKBOX's music recommendations also adopt relevant strategies. The core insight of the KKBOX team is that the value of recommendation systems lies not only in "guessing what users like", but also in "helping users discover unexpected joys". Simply pursuing accuracy can easily lead to information silos, allowing users to only access content that they already have preferences for.

In the process of integrating with Amazon Personalize, KKBOX has established an evaluation system that goes beyond traditional accuracy, introducing four key indicators: diversity (the range of songs or artists covered by recommendation results), novelty (recommending obscure content that users may not have heard of but may like), serendipity (recommending content that differs from users' historical preferences but still surprises them), and coverage (the proportion of the recommendation system that can reach the overall content library) [8].

Under the guidance of the above indicators, KKBOX achieved a weekly full listening user ratio of 84.97%, and a playback conversion rate of 78.30% after users click on recommended content. Meanwhile, due to the increased level of model automation, operating costs and manpower requirements have been reduced by approximately 70%. The implementation of this framework has successfully transformed the abstract concept of 'user satisfaction' into quantifiable technical indicators. The traditional click through rate cannot measure whether users are truly satisfied, and the introduction of indicators such as diversity and novelty enables recommendation systems to enhance long-term user stickiness while activating exposure opportunities for niche music and emerging artists, alleviating the long tail dilemma in the content ecosystem. Similarly, there is a natural "seesaw" effect between accuracy and diversity: increasing diversity may lower click through rates in the short term. The solution of KKBOX relies on fine hyperparameter tuning, which is difficult to directly reuse in different business scenarios. In addition, diversity indicators are essentially calculated offline, and whether users are truly surprised by unfamiliar recommended content still needs to be verified through online A/B testing. This means that system optimization still requires a lot of online experimental support.

3.3. Intelligent Pricing and Promotion: Personalized Coupon Distribution Strategy

The traditional coupon distribution strategy is often static, such as providing the same discount to all users or pushing it to a fixed audience at a fixed time point. Meituan has built an end-to-end real-time coupon allocation system, which is innovative in three aspects: firstly, using Isotonic Regression to ensure that the predicted conversion rate monotonically increases with the coupon denomination - this is a common sense requirement, but it is easily violated in ordinary machine learning models; Secondly, the Lagrange dual algorithm is used to calculate the optimal coupon denomination within 50 milliseconds based on the user's real-time characteristics and current budget constraints; Thirdly, introduce a closed-loop control mechanism to dynamically adjust the subsequent user discount based on budget consumption progress, ensuring that the overall budget is not exceeded.

As of May 2024, the system has covered more than 110 major cities in China and served over 100 million users. Bringing an additional annual profit of approximately 8 million RMB to Meituan, mainly due to improved conversion rates and revenue growth. Large scale online experiments have shown that this algorithm significantly outperforms traditional methods in both conversion rate and revenue dimensions. This case demonstrates the possibility of achieving millisecond level personalized decision-making under hard budget constraints. It combines the conversion rate prediction model in machine learning with the Lagrangian dual optimization in operations research, forming a complete technical chain that can be engineered and deployed [9].

As the system runs, some users may learn to "manipulate" the system, such as placing orders only when they receive high discount coupons. This strategic behavior requires the model to be continuously updated to maintain effectiveness. In addition, the optimization goals of the system mainly focus on current conversions and instant income, and frequent distribution of personalized coupons may weaken users' willingness to pay at the original price when not using coupons. How to incorporate user lifecycle value into real-time decision-making frameworks remains an unresolved research topic.

3.4. Automated content production: thousands of people and faces generating advertising creativity

Traditional video advertising production costs are high, and a professional advertisement often requires thousands of dollars and several weeks of time. The core breakthrough of MAGE (Marketing Asset Generation Engine) lies in the ability to automatically generate over 700 million different video ad variations based solely on a single music track and album cover, each of which can reflect the artist's visual style.

This technology is not just a simple template replacement, but can create video advertisements with diverse content while maintaining brand consistency, thus supporting true "thousands of people, thousands of faces" advertising - different users can see different styles of advertising versions.

Compared to manually designed advertisements, AI generated advertisements reduce production costs by approximately 98%. On TikTok and Meta platforms, the average click through rate of these ads is 17% higher than that of human designer works. The engine generated advertising materials for 33 real music tracks and accumulated over 11 million exposures in 72 marketing campaigns. This case highlights the enormous potential of generative AI in large-scale personalized creativity. Human designers cannot create hundreds of different styles of advertisements for each song and audience at a reasonable cost, but AI can do it. The study also found that an independent AI selection system can predict which generated versions perform better for specific audiences before advertising placement, laying the foundation for achieving a fully automated "generation screening placement" loop [10].

Although AI generated advertisements perform well on surface metrics such as click through rates, research has not shown that they can convey the subtle emotions, cultural metaphors, or brand stories injected by human designers. This may have an impact on the long-term accumulation of brand assets. Meanwhile, the training data for generative AI comes from existing works, and there is still legal controversy over whether the generated advertisements constitute infringement or derivative works. In addition, if a large number of brands use similar generative models and training data, advertising creativity may exhibit "AI style" homogenization, which in turn weakens the brand's differentiation competitiveness.

4. Business Value and Consumer Impact

The three optimisers of the company's targets are to improve conversion rate (CR), decrease cost per customer acquisition (CAC), and enhance analysis of customers' value changes over time (CLV). The above measures will help reduce the amount of information that needs to be learned by the public and make purchases more convenient. However, there are also some negative consequences of this; for example, users may develop psychological resistance, feel the pressure of being observed, and also experience the phenomenon of information cocoons, being exposed to only a narrow range of information for an extended period. Strengthen the operating efficiency and user experience of the company with a strategy, and also watch out for potential psychological and information-environment risks.

5. Current Challenges

Since most of the current marketing systems are complex "black box" models, when there is a deviation in marketing decisions, it is difficult to track how this was done and explain the reasons for the recommendation results to users. There will be an even greater problem of lack of transparency in the fairness of algorithms. If there are biases in the training data or the model design itself, the algorithm will also have differential pricing for different groups of people. Therefore, a review mechanism will be introduced to address and correct such unfairness by the company.

In addition to the above problems directly related to algorithms, there are also issues with the emotion of automation. Although the efficiency-improving functions of automation are well-known, they may fail to convey the desired message of brand communication effectively. The second problem that enterprises need to address in promoting the application of technology is how to preserve the humanistic warmth of the brand in algorithmic recommendations, automated customer service.

6. Future Trends and Research Directions

Multimodal fusion is a current technology for the future direction and research direction. The aim of this way is to combine all kinds of information, such as voice, pictures and text, to provide users with a richer sense of personalisation.

At the same time, edge computing and privacy computing are also being used to address data security issues. Among them, federated learning is representative, and it can conduct the training and update of personalised models without uploading or centralising user data to achieve both privacy protection and marketing effectiveness.

Virtual Marketing Spaces and the Rise of the Metaverse are New Scenarios for Brand Interaction. Now that artificial intelligence technology is available, virtual people who can communicate with users on an intimate and personal level through brands have been developed. This interactive form does not follow the old way of marketing and is more engaging for users.

However, although the above technologies are available, humans will still be needed for marketing work. On the contrary, human-machine cooperation is creating a new model of work. The Tasks of marketers will gradually shift from specific implementation activities to tuning and managing artificial intelligence systems. Learn to use the model for output generation, adjust algorithm parameters, ensure the effectivity and ethics of marketing activities.

7. Conclusion

This paper will systematically review the technical structure, main application cases, economic value and psychological effect on consumers of artificial intelligence in personalised marketing, and analyze the existing problems, such as low algorithm transparency, privacy risks, information cocoons, and a decrease in brand humanistic warmth. Research has shown that artificial intelligence can enhance the conversion rate and user retention of a platform, increase the diversity of content, reduce operating costs, etc.; at the same time, problems in ethical responsibility have not been solved.

A three-dimensional analysis framework of "technology value ethics" was built in this paper to provide practical support for evaluating the path of technology and identifying risks in enterprise marketing. Looking ahead to the future, personalised marketing will continue to develop under the leadership of multimodal fusion and privacy computing technologies, and the coordinated progress of technological innovation and ethical governance will be necessary for the sustainable development of personalised marketing.

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