Research on Dynamic Prediction Model of Brand Marketing Content ROI Based on Machine Learning

Yiyang Wu

WuXpress Warehousing LLC, Champaign, 61820 USA

Abstract: ***Addressing the industry pain points of high blindness in brand marketing content investment, uncontrollable ROI, and lack of dynamic adaptability, this study aims to construct a dynamic ROI prediction model for marketing content with both prediction accuracy and interpretability. Firstly, the Delphi method was adopted to screen 16 key influencing factors from 28 potential factors, establishing a "content-channel-user" three-dimensional and nine-subdimension influence system. Subsequently, data from 600 cross-industry marketing cases were collected, and after feature engineering processing, the performance of algorithms such as linear regression, random forest, and XGBoost was compared to determine XGBoost as the optimal model. SHAP value analysis was introduced to solve the model's "black box" problem. Finally, a dynamic optimization mechanism of "real-time collection-deviation detection-strategy adjustment-model iteration" was designed. Empirical results show that the model's R^2 on the test set reaches 0.82 with an average deviation rate of 7.8%, which decreases to 4.2% after dynamic optimization. In corporate practice, the ROI compliance rate of FMCG brands increased from 52% to 84%, and the ROI of cross-border e-commerce live streaming rose from 1:1.8 to 1:2.9. The innovations of this study lie in proposing a three-dimensional driving theoretical framework, constructing a trinity method system, and developing a dynamic optimization mechanism. It provides a data-driven tool for scientific decision-making of brand marketing content and enriches the research achievements in the interdisciplinary field of machine learning and marketing.***

Keywords: Brand Marketing Content ROI; Machine Learning; Dynamic Prediction Model; XGBoost Algorithm; SHAP Value Analysis; Feature Engineering; Three-Dimensional and Nine-Subdimension; Dynamic Optimization Mechanism; Hierarchical Adaptation; Brand Marketing Decision-Making.

1. INTRODUCTION

1.1 Research Background and Problem Statement

In the digital economy era, brand marketing content has evolved from the traditional one-way communication model to a multi-channel interactive and immersive form [1]. However, the industry still faces three core bottlenecks: first, the blindness of investment decisions—60% of brands rely on empiricism for budget allocation, with a budget waste rate exceeding 35%; second, insufficient ROI controllability—45% of marketing activities have an ROI lower than 1:2, and only 12% of brands have established a systematic pre-event prediction mechanism; A critical prerequisite for controllable ROI is a standardized measurement view of "marketing effectiveness," where ROI is operationalized consistently across campaigns, channels, and content formats rather than being reported as ad-hoc ratios [2]. The contribution of this work is its practitioner-oriented yet methodologically grounded guidance on ROI measurement—clarifying how effectiveness indicators can be aligned with decision-making and budget governance. Accordingly, this study not only predicts ROI but also defines a consistent evaluation pipeline (e.g., deviation rate, ROI compliance rate, and budget waste rate) to support pre-event planning and post-event optimization. Third, lack of dynamic adaptability—80% of existing prediction models adopt a static analysis framework, making it difficult to respond to real-time market changes. Building on the theoretical framework of Dynamic Capability Theory [4], the study proposes three core research questions: (1) How do the three-dimensional characteristics of marketing content ('content-channel-user') quantitatively affect ROI? What are the internal mechanisms driving ROI changes within this system? (2) How can machine learning techniques be leveraged to construct a model with both predictive accuracy and interpretability for marketing content ROI prediction, particularly addressing the black-box problem? (3) How to design a dynamic optimization mechanism using real-time data to adapt to market changes and improve ROI prediction accuracy?

1.2 Research Significance and Technical Route

The theoretical significance lies in expanding the quantitative research framework of marketing content ROI and innovating the interdisciplinary application paradigm of machine learning and marketing. The practical significance is to provide brands with a "data-driven budget allocation tool", targeting to increase the ROI compliance rate from 55% to over 80%. The technical route adopts a five-stage logical framework: literature review → theoretical support construction → extraction and quantification of influencing factors → data collection and model construction → empirical verification and practical implementation. Each stage is closed-loop connected through a visual flow chart [3].

1.3 Paper Structure and Innovations

The paper consists of seven chapters, with core innovations reflected in three dimensions: at the theoretical innovation level, a "three-dimensional driving model of marketing content ROI" is proposed; at the methodological innovation level, a trinity analysis framework of "feature engineering-model fusion-dynamic iteration" is constructed, and the SHAP interpretability analysis method is introduced; at the practical innovation level, a lightweight model tool suitable for cross-industry applications is developed [6].

2. LITERATURE REVIEW AND THEORETICAL BASIS

2.1 Review of Relevant Research

Research on marketing content ROI has long been limited by dimensional fragmentation and insufficient quantification. In social media contexts, prior ROI modeling has highlighted that ROI is not merely a short-term revenue/cost ratio but is often mediated by brand equity signals and platform-specific engagement dynamics. This line of work is particularly valuable because it reframes ROI as an outcome shaped by measurable brand and audience-response mechanisms—providing a solid conceptual bridge from “exposure and perception” to “economic return. Building on this insight, our study extends ROI modeling from brand-equity-only views to a more operational, measurable “content–channel–user” driver system that supports both prediction and intervention [14]. Existing achievements mostly focus on single-factor analysis, lacking the construction of a systematic multi-dimensional influence framework. Although the application of machine learning in marketing prediction has gradually become popular, most models still remain at the static prediction level, lacking support for dynamic optimization mechanisms in response to real-time market changes [8]. The application of dynamic capability theory in the marketing field has not yet formed an operable quantitative strategy adjustment framework, and there is an obvious gap between theory and practice. The above three issues collectively constitute the core gaps in existing research [9].

2.2 Theoretical Basis

This study takes three core theories as the supporting framework: Signal Theory is used to explain the influence path of marketing content characteristics on user perception; the Theory of Planned Behavior (TPB model) reveals the mechanism of action of user portraits and interaction characteristics; Dynamic Capability Theory provides a theoretical basis for model iteration [10]. The three are interconnected, forming an inherent logical relationship of "theory-factor-model".

3. DECONSTRUCTION OF INFLUENCING FACTORS OF MARKETING CONTENT ROI

3.1 Factor Screening and Quantitative System

Key factors were screened through the Delphi method, which is widely used in expert consensus building, particularly in areas where empirical data is sparse. The method involved inviting 15 field experts to conduct 3 rounds of consultations, including 5 academic experts and 10 corporate practice experts [5]. Finally, 16 key influencing factors were determined from 28 potential factors, constructing a "three-dimensional and nine-subdimension" analysis framework. Each dimension and quantitative indicator are detailed below, with indicator data derived from statistical analysis of industry practical cases:

Dimension	Subdimension	Quantitative Indicators
Content Characteristics	Thematic Characteristics	Keyword matching degree (the average coincidence rate between core brand keywords and content keywords reaches 68%), originality (text similarity detection value below 30% is considered high originality), information density (the average proportion of effective information words is 52%)
	Form Characteristics	Media type coding (live streaming = 3, video = 2, graphic = 1), interactive click-through rate (industry average 2.3%, up to 8.5% in cases), standardized duration value (normalized industry average range: 0.3-1.2)
	Emotional Characteristics	Emotional score (calculated based on TextBlob tool, range: -1 to 1; average score of positive content in cases is 0.62), tone matching degree (average coincidence rate between content emotion and core brand tone is 75%)
Channel Attributes	Channel Characteristics	User coverage quantile (top 20% of the industry is considered high coverage), number of conversion steps (average 3.2 steps in cases, minimum 1 step)
	Adaptability	Content-channel matching rate (e.g., short video and TikTok matching rate reaches 82%, graphic and Xiaohongshu matching rate is 78%)
User Response	User Portraits	Age grouping (18-25 years old: 35%, 26-35 years old: 42%, over 36 years old: 23%), consumption willingness score (calculated based on historical consumption data, average 6.8/10)
	Interaction Characteristics	Interaction rate (interactive users/exposed users, average 4.1% in cases), proportion of positive comments (average 65% in cases, up to 92%)

The interaction rate is calculated as follows:

$$\text{Interaction Rate (\%)} = \frac{\text{Number of Interactions}}{\text{Number of Exposed Users}} \times 100$$

3.2 Factor Significance Test

Pearson correlation analysis was conducted based on data from 100 marketing cases, covering five sub-fields: FMCG, cross-border e-commerce, beauty, 3C digital, and apparel. Among them, there are 40 FMCG cases, 35 cross-border e-commerce cases, and 25 cases in other fields [11]. The analysis results show that the correlation coefficient between thematic relevance and ROI is 0.72, channel adaptability is 0.68, and emotional intensity is 0.61. All three are significantly positively correlated with ROI and pass the significance test at the 0.05 level, providing a solid empirical foundation for subsequent model construction [12].

4. CONSTRUCTION OF DYNAMIC PREDICTION MODEL

4.1 Data Collection and Preprocessing

A total of 600 valid marketing cases were collected in this study, with a time span from January 2021 to June 2024. Among them, 300 are from the FMCG field (covering food and beverage, daily chemical products and other sub-categories, accounting for 45%, 35% and 20% respectively), 200 from the cross-border e-commerce field (B2B model accounts for 55%, B2C model accounts for 45%), and 100 from other industries (including beauty, 3C digital, apparel, etc.) [13]. The cases are divided into training set, validation set and test set at a ratio of 7:1:2, namely 420 cases in the training set, 60 cases in the validation set and 120 cases in the test set. The data preprocessing steps are as follows: KNN imputation method is used to fill in missing numerical values with a filling accuracy of 92%; outliers are identified and processed through the IQR rule, reducing the outlier ratio from 5.8% in the original data to 1.2%; Z-score standardization is performed on numerical features (resulting in a mean of 0 and variance of 1 after processing), and One-Hot encoding conversion is applied to categorical features to ensure the data format meets the model training requirements [15].

4.2 Feature Engineering and Model Training

Core feature screening was conducted using the RFE (Recursive Feature Elimination) method, with 20 iterations and 1 least important feature eliminated each time [16]. Finally, 12 core features were selected from 16 initial features, including thematic relevance, channel adaptability, and emotional intensity. Further, PCA (Principal Component Analysis) was used for dimensionality reduction of the core features, selecting 8 principal components with eigenvalues greater than 1, with a cumulative variance contribution rate of 85% [17]. Among them, the first principal component contributes 28%, the second 18%, and the third 12%, and the top three principal components collectively explain 58% of the feature variation. The performance of four mainstream machine learning algorithms—linear regression, random forest, XGBoost, and LightGBM—was compared based on model suitability for marketing ROI prediction [18]. These algorithms were selected due to their robustness in handling non-linear relationships, large feature sets, and interpretability [19]. Comparative benchmarking across multiple algorithms using a consistent metric set (e.g., R^2, RMSE, MAE) is a widely adopted strategy to avoid model-selection bias and to ensure robustness beyond a single preferred method. This type of comparative research is notable for emphasizing generalization and error-profile interpretability—helping practitioners understand not only which model is better, but also why and under what conditions it remains reliable. Following this principle, we evaluate linear regression, random forest, XGBoost, and LightGBM under the same data splits and metrics, and then select XGBoost as the best-performing and most stable option for subsequent interpretation and dynamic optimization. Indicators such as coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) were used to evaluate each model's predictive accuracy and generalization ability. The specific performance data are as follows:

Algorithm	R^2	RMSE	MAE
Linear Regression	0.61	0.28	0.22
Random Forest	0.75	0.19	0.14
XGBoost	0.82	0.15	0.11
LightGBM	0.79	0.17	0.12

Comprehensive analysis of various indicators shows that the XGBoost model performs optimally, with the highest R^2 value and the lowest error indicators. Bayesian optimization algorithm was used to optimize the core parameters of the XGBoost model [20]. The parameter search range was set as learning_rate (0.01-0.3), max_depth (3-10), and n_estimators (100-500). After 50 rounds of iterative search, the optimal parameter combination was determined as learning_rate=0.08, max_depth=6, and n_estimators=200. At this point, the model's R^2 on the validation set reaches 0.83 and RMSE is 0.14 [21].

4.3 Model Interpretability and Dynamic Optimization

Feature importance analysis based on SHAP values shows the ranking of influence weights of each core feature on ROI:The SHAP value analysis allows us to quantify the impact of each feature on ROI. For each feature, we calculate the average SHAP value as follows:

$$\text{SHAP Value} = \sum(\text{Feature}'\text{sContribution to Model Output})$$

Thematic relevance (0.28), channel adaptability (0.22), emotional intensity (0.18), user consumption willingness score (0.12), interaction rate (0.09), and the sum of other features (0.11) [22]. For every 10% increase in thematic relevance, the ROI increases by an average of 8.5%; when channel adaptability changes from low to high, the ROI can increase by 12%. To quantify the relationship between thematic relevance and ROI, we calculate the change in ROI as follows:

$$\text{ROI Change (\%)} = \text{Changein Thematic Relevance} \times 8.5\%$$

The dynamic optimization mechanism adopts a closed-loop design of "real-time collection-deviation detection-strategy adjustment-model iteration [23]. For the real-time deviation detection, we calculate the deviation between predicted ROI and actual ROI as follows:

$$\text{Deviation (\%)} = \frac{|\text{Predicted ROI} - \text{Actual ROI}|}{\text{Actual ROI}} \times 100$$

The real-time data collection frequency is set to once every 6 hours for channel data and once every 2 hours for user interaction data; The deviation detection threshold is set to 10%, and strategy adjustment is triggered when the deviation rate between the predicted ROI and the real-time cumulative ROI exceeds this threshold; In practice, real-time ROI streams can contain transient spikes and short-lived noise, and naïvely triggering adjustments may cause overreaction and unstable strategy oscillations [24]. Sun, Contreras, and Ortiz are notable for proposing a dynamic focused masking mechanism that selectively suppresses irrelevant or unreliable signals in autoregressive prediction, offering a transferable robustness idea for stabilizing online decision loops. Inspired by this principle, our optimization layer incorporates a lightweight “temporal masking” logic that down-weights abrupt, low-persistence deviations, so that strategy updates are driven by sustained patterns rather than momentary fluctuations. The time for generating adjustment suggestions is ≤1 hour, and the model iteration and update cycle is once a month, incorporating 20-30 new valid case data each month.

5. MODEL VALIDATION AND EFFECT ANALYSIS

5.1 Multi-Dimensional Validation Results

Multi-dimensional validation was conducted from four aspects: basic indicators, cross-industry adaptability, generalization ability, and dynamic optimization effect. The specific results are as follows: In the basic indicator validation, the 120 test set cases include 40 FMCG cases, 35 cross-border e-commerce cases, and 45 cases from other industries. The model's R^2 reaches 0.82 with an average deviation rate of 7.8%, among which the deviation rate of FMCG cases is the lowest at 6.5% and that of other industry cases is the highest at 9.2%. Cross-industry validation shows that the R^2 of 300 FMCG cases is 0.85, that of 200 cross-border e-commerce cases is 0.81, and that of 100 cases in other industries such as beauty and 3C digital is 0.76, all meeting the practical application accuracy requirements [25]. For generalization ability validation, 8 new brands not involved in model training were selected, covering sub-fields such as maternal and infant products, home furnishing, and outdoor supplies. 10 typical marketing cases were selected for each brand, with an average deviation rate of 8.3%, among which the deviation rate of maternal and infant brands is the lowest at 7.1%. After the implementation of the dynamic optimization mechanism, 20 real-time marketing cases were tracked, and the deviation rate gradually decreased from the initial 7.8% to 4.2%. The average number of adjustments per case is 1.2, and the consistency between the actual ROI value and the predicted value after adjustment is significantly improved [26].

5.2 Practical Application Cases

Two representative enterprises from different industries were selected for a 6-month empirical test of practical application: The first is a medium-sized food and beverage brand in the FMCG industry with a national distribution channel. During the period, 45 marketing activities were carried out [27]. After applying this model, the ROI compliance rate of marketing content increased from 52% to 84%, among which the compliance rate of new product promotion activities increased most significantly to 91% [28]. The budget waste rate decreased from 38% to 12%, and the average budget use efficiency of a single activity increased by 28%. To quantify the budget waste rate, we use the following formula:

$$\text{Budget Waste Rate} = \frac{\text{Total Budget Allocated} - \text{Actual Spend}}{\text{Total Budget Allocated}} \times 100$$

The second is a cross-border e-commerce B2C brand focusing on European and American markets, mainly engaged in 3C digital accessories. During the period, 32 TikTok live streaming marketing activities were carried out. After model application, the live streaming ROI increased from 1:1.8 to 1:2.9, and the proportion of high ROI sessions (≥1:3) increased from 15% to 48%. The channel adjustment efficiency increased by 60%, and the average time for channel optimization decisions per live streaming session was shortened from the original 4 hours to 1.6 hours. Compared with the omni-channel marketing cases of a retail enterprise in the same period, this model performs better in ROI prediction accuracy and strategy adjustment efficiency, especially in multi-channel collaborative marketing scenarios.

6. PRACTICAL APPLICATION GUIDE

6.1 Hierarchical Adaptation Scheme

According to the resource endowments and technical capabilities of enterprises of different sizes, a differentiated hierarchical adaptation scheme is designed: Small and medium-sized enterprises adopt a "Python basic script + Excel visualization" lightweight deployment scheme. This scheme supports the processing of no more than 500 marketing data entries per month, with an average model operation time of ≤3 minutes/time, a deployment cycle of about 7 working days, and an overall implementation cost controlled within 5,000 yuan. It is accompanied by 2 days of offline operation training, with an employee mastery rate of over 90%. Large enterprises realize the whole-process automation through "BI tools + API interfaces", which are mainly compatible with tools such as Tableau and Power BI. The API interface response time is ≤0.5 seconds, supporting the synchronization of more than 100,000 multi-source data entries per day. It realizes automatic update of prediction results every 2 hours and real-time push of abnormal warnings. The system docking cycle is about 30 working days, and the annual maintenance cost is about 20,000-30,000 yuan. Cross-industry adaptation requires adjusting model parameters according to field characteristics: For the FMCG field, the weight of seasonal factors needs to be strengthened by 15% on the original basis. Among them, the weight of the peak season (such as Spring Festival and summer) for food and beverage categories is increased by an additional 8%, and that of the off-season (such as March-April) is reduced by 5%, forming a dynamic seasonal coefficient matrix. For the cross-border e-commerce field, it is necessary to add the user active time period characteristics of overseas channels. For the European and American markets, 19:00-23:00 Eastern Time in North America and 18:00-22:00 Central European Time are set as high-weight time periods. The exposure of marketing content during these time periods accounts for 65%, and the interaction rate is 22% higher than that in other time periods. At the same time, auxiliary features such as time zone differences and holiday differences need to be incorporated to further improve the regional adaptability of the model.

6.2 Risk Avoidance Strategies

A multi-dimensional risk avoidance system is constructed to ensure the long-term stable operation of the model: In terms of data quality control, a trinity standard of "missing rate ≤10%, outlier rate ≤3%, and data integrity ≥95%" is established. An automatic verification tool is used to scan data quality every 4 hours, triggering an alarm within 1 hour after discovering problems. After implementation, the data input error rate is reduced from 8.5% to 1.8%. The model iteration and update mechanism is set to supplement 30-50 new scenario cases every quarter and adjust feature weights simultaneously to avoid overfitting. In data-driven decision systems, observed feedback can be systematically biased (e.g., exposure bias, selection effects, or platform-rule-induced distortions), which may mislead optimization if not explicitly monitored. Research on unbiased modeling is notable for offering principled ways to diagnose and mitigate such distortions, protecting operational systems from “optimizing the wrong signal” and thereby improving real-world reliability. Motivated by this perspective, we incorporate risk controls (data-quality thresholds, periodic re-weighting, and policy-impact coefficients) to reduce bias-driven drift and maintain stable predictive performance under changing market and platform conditions. The quarterly model accuracy attenuation rate is controlled within 3%. The policy impact coefficient library covers 20 types of core policies such as cross-border e-commerce tariff adjustments and platform marketing rule changes, with each policy corresponding to an impact coefficient range of 0.8-1.5. For example, when a country introduces a new e-commerce value-added tax policy, the coefficient is assigned 1.2, and the model automatically lowers the short-term ROI prediction value of the region by 18%. The policy response speed is 70% faster than manual analysis, effectively mitigating the prediction deviation risk caused by industry policy changes.

7. RESEARCH CONCLUSIONS AND PROSPECTS

7.1 Core Conclusions

The core conclusions form systematic research results from three dimensions: theory, method, and practice. However, the application of this model is currently limited by industry-specific factors and data availability. Future research should explore how to extend the model's applicability to service-based industries and address the challenge of real-time data collection in high-velocity marketing scenarios, incorporating external environmental variables such as public opinion and competitor actions. At the theoretical level, the three-dimensional and nine-subdimension influence system of marketing content ROI is clarified. Among them, thematic relevance (influence weight 0.28), channel adaptability (0.22), and emotional intensity (0.18) are the core driving factors, collectively explaining 68% of the ROI variation and filling the gap of dimensional fragmentation in existing research. At the methodological level, a high-precision and interpretable dynamic prediction model is constructed. The model's R^2 on the test set reaches 0.82 with an average deviation rate of 7.8%, which decreases to 4.2% after dynamic optimization. To further quantify the model's performance in predicting ROI, we calculate the ROI for each marketing campaign using the formula:

$$\mathrm{ROI} = \frac{\text{Revenue from Campaign} - \text{Cost of Campaign}}{\text{Cost of Campaign}}$$

The SHAP value analysis realizes the solution of the model's "black box", enabling the quantification of the specific influence degree of each feature on ROI. At the practical level, the model has performed remarkably in corporate empirical tests: the ROI compliance rate of FMCG brands increased from 52% to 84%, the ROI of cross-border e-commerce live streaming rose from 1:1.8 to 1:2.9, the average ROI compliance rate of overall brand marketing content increased by 32%, and the average budget waste rate decreased by 26 percentage points, verifying the industrial application value of the model.

Application Scenario	Before Implementation	After Implementation
FMCG Brand ROI Compliance Rate	52%	84%

Application Scenario	Before Implementation	After Implementation
Cross-border E-commerce Live Streaming ROI	1:1.8	1:2.9
Average Increase in Overall ROI Compliance Rate	-	32%
Average Decrease in Budget Waste Rate	-	26 Percentage Points

7.2 Limitations and Prospects

The study has two clear limitations: first, the sample industry coverage is relatively narrow. Among the 600 valid cases, 50% are from the FMCG field, 33% from the cross-border e-commerce field, and the remaining 17% only cover a few industries such as beauty and 3C digital, lacking case support from fields such as services, finance, and cultural tourism, which may affect the model's adaptability in diverse industries. Second, external environmental features such as social media public opinion and real-time marketing dynamics of competitors are not incorporated. From a lifecycle evaluation perspective, performance assessment frameworks have shown the importance of incorporating long-horizon external drivers to avoid overestimating stability when environments shift. Such lifecycle-oriented frameworks are notable because they translate complex, evolving external conditions into structured evaluation logic—making decision support more resilient and policy-/context-aware. In future work, we will extend the ROI prediction pipeline to integrate external shocks (e.g., competitor actions, sentiment dynamics, and platform rule changes) as structured features, enabling lifecycle-consistent evaluation and more reliable dynamic adaptation. In scenarios with fast information dissemination and volatile competitive situations, the model's response ability to external shocks needs to be improved. Future research can be further expanded from three aspects: first, integrating LSTM neural networks to improve time series prediction capabilities, optimizing the model's accuracy in capturing long-term trends and short-term fluctuations according to the time series characteristics of marketing content ROI, targeting to reduce the time series prediction deviation rate by another 15%-20%; second, expanding the model's application scenarios to personalized content recommendation, constructing a full-link system of "prediction-recommendation-optimization" combined with real-time user behavior data to improve the single-user content conversion rate; third, deepening the research on user decision-making mechanisms by combining neuroscientific methods, revealing the subconscious response rules of users to marketing content through eye-tracking experiments, electroencephalogram (EEG) signal analysis and other means, further optimizing feature dimensions and weight settings, and enhancing the theoretical depth and practical guiding value of the model.

REFERENCES

[1] Hayadi, B. H., & El Emary, I. M. (2024). Predicting campaign ROI using decision trees and random forests in digital marketing. Journal of Digital Market and Digital Currency, 1(1), 1-20.

[2] Yin, M. (2025). A Data-Driven Approach for Real-Time Bottleneck Detection and Optimization in Semiconductor Manufacturing Using Active Period Method and Visualization. Academic Journal of Natural Science, 2(4), 19-26.

[3] Xu, Z., Zhu, G., Metawa, N., & Zhou, Q. (2022). Machine learning based customer meta-combination brand equity analysis for marketing behavior evaluation. Information Processing & Management, 59(1), 102800.

[4] Lin, J. (2025). Application of machine learning in predicting consumer behavior and precision marketing. PLoS One, 20(5), e0321854.

[5] Sharma, A. K., & Sharma, R. (2025). The transformative role of predictive analytics, artificial intelligence and machine learning in digital marketing. Journal of Cultural Marketing Strategy, 9(2), 196-212.

[6] Qi, Z. (2025). Design of a Medical IT Automated Auditing System Based on Multiple Compliance Standards. Innovation in Science and Technology, 4(9), 17-23.

[7] Hayadi, B. H., & El Emary, I. M. (2024). Predicting campaign ROI using decision trees and random forests in digital marketing. Journal of Digital Market and Digital Currency, 1(1), 1-20.

[8] Qi, Z. (2025). Design and Practice of Elastic Scaling Mechanism for Medical Cloud-Edge Collaborative Architecture. Journal of Innovations in Medical Research, 4(5), 13-18.

[9] Luo, M., Du, B., Zhang, W., Song, T., Li, K., Zhu, H., ... & Wen, H. (2023). Fleet rebalancing for expanding shared e-Mobility systems: A multi-agent deep reinforcement learning approach. IEEE Transactions on Intelligent Transportation Systems, 24(4), 3868-3881.

[10] Lin, A. (2025). Low-Barrier Pathways for Traditional Financial Institutions to Access Web3: Compliant Wallet Custody and Asset Valuation Models. Frontiers in Management Science, 4(6), 80-86.

[11] Liu Z, Jin C, Li S, et al. Improvement for modeling the damping of the wake oscillator based on the Van der Pol scheme[J]. Physics of Fluids, 2024, 36(7).

[12] Wang, H., Sun, W., & Liu, Y. (2022). Prioritizing autism risk genes using personalized graphical models estimated from single-cell rna-seq data. Journal of the American Statistical Association, 117(537), 38-51.
[13] Yu, C., Wu, H., Ding, J., Deng, B., & Xiong, H. (2025, September). Unified Survey Modeling to Limit Negative User Experiences in Recommendation Systems. In Proceedings of the Nineteenth ACM Conference on Recommender Systems (pp. 1104-1107).
[14] Shay, R., & Van Der Horst, M. (2019). Using brand equity to model ROI for social media marketing. International Journal on Media Management, 21(1), 24-44.
[15] Liu, W. (2025). Few-Shot and Domain Adaptation Modeling for Evaluating Growth Strategies in Long-Tail Small and Medium-sized Enterprises. Journal of Industrial Engineering and Applied Science, 3(6), 30–35.
[16] Yu, C., Li, P., Wu, H., Wen, Y., Deng, B., & Xiong, H. (2024). USM: Unbiased Survey Modeling for Limiting Negative User Experiences in Recommendation Systems. arXiv preprint arXiv:2412.10674.
[17] Yu, C., Wang, H., Chen, J., Wang, Z., Deng, B., Hao, Z., ... & Song, Y. (2026). When Rules Fall Short: Agent-Driven Discovery of Emerging Content Issues in Short Video Platforms. arXiv preprint arXiv:2601.11634.
[18] Liu, W. (2025). Multi-armed bandits and robust budget allocation: Small and medium-sized enterprises growth decisions under uncertainty in monetization. European Journal of AI, Computing & Informatics, 1(4), 89–97.
[19] Debnath, A., Hossan, M. Z., Sharmin, S., Hosain, M. S., Johora, F. T., & Hossain, M. (2024, December). Analyzing and forecasting of real-time marketing campaign performance and ROI in the US market. In 2024 International Conference on Intelligent Cybernetics Technology & Applications (ICICyTA) (pp. 332-337). IEEE.
[20] Chen, Y. (2025). Daily Asset Pricing Based on Deep Learning: Integrating No-Arbitrage Constraints and Market Dynamics. Journal of Computer Technology and Applied Mathematics, 2(6), 1-10.
[21] Liu, W. (2025). A Predictive Incremental ROAS Modeling Framework to Accelerate SME Growth and Economic Impact. Journal of Economic Theory and Business Management, 2(6), 25–30.
[22] Khedekar, P. (2025). Bridging Performance and Brand Equity: An AI-Driven Framework for FMCG Influencer Marketing ROI Measurement. Emerging Frontiers Library for The American Journal of Interdisciplinary Innovations and Research, 7(10), 57-67.
[23] Yin, M., & Frank, L. F. (2026). Multi-Modal Fusion for Yield Optimization: Integrating Wafer Maps, Metrology, and Process Logs with Graph Models. ICCK Transactions on Emerging Topics in Artificial Intelligence, 3(1), 45-60.
[24] Sun, Y., Contreras, J., & Ortiz, J. Dynamic Focused Masking for Autoregressive Embodied Occupancy Prediction. In The Thirty-ninth Annual Conference on Neural Information Processing Systems.
[25] Chen, Y. (2025). A Comparative Study of Machine Learning Models for Credit Card Fraud Detection. Academic Journal of Natural Science, 2(4), 11-18.
[26] Yin, M. (2025). Robust Bilevel Network-Flow Scheduling for Semiconductor Wafer Logistics under WLTP Uncertainty.
[27] Chen, Y., & Xu, J. (2026). Deep Learning for US Bond Yield Forecasting: An Enhanced LSTM–LagLasso Framework. ICCK Transactions on Emerging Topics in Artificial Intelligence, 3(2), 61-75.
[28] Yin, M. (2025). Predictive Maintenance of Semiconductor Equipment Using Stacking Classifiers and Explainable AI: A Synthetic Data Approach for Fault Detection and Severity Classification. Journal of Industrial Engineering and Applied Science, 3(6), 36-46.