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Research on Attribution Modeling, Revenue Evaluation, and Large Language Model Fine-Tuning Frameworks for Marketing Technology Platforms

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Abstract: To address the challenges of complex multi-touchpoint interaction chains, ambiguous channel contribution boundaries, fragmented revenue measurement dimensions, and insufficient utilization of marketing semantic information in marketing technology platforms, this paper proposes a unified research framework for attribution modeling, revenue assessment, and fine-tuning of a large language model. This method first constructs a joint representation mechanism based on user interaction sequences, channel contact signals, and time-related features, characterizing the contextual associations and temporal dependencies of marketing behavior in a unified representation space. Then, it models the role of different marketing touchpoints through a context-aware attention mechanism and contribution scoring strategy, and achieves a stable allocation of multi-touchpoint contributions through attribution normalization. Based on this, the attribution results are further mapped to revenue-related objectives, forming a comprehensive analytical path from behavioral understanding to value quantification. Simultaneously, this paper incorporates fine-tuning of a large language model into the overall framework to enhance the model's understanding of marketing texts, business contexts, and platform rules, thereby improving the semantic support level in the attribution analysis and revenue characterization processes. Related research results show that the method presented in this paper can more effectively complete key touchpoint identification, value association modeling, and unified decision representation learning in marketing technology platform scenarios, providing a new methodological foundation for digital marketing analysis, platform intelligent evaluation, and refined resource allocation.

Keywords: Marketing technology platform; multi-touchpoint attribution; revenue quantification; semantic augmentation modeling.

1. Introduction

As the digital economy continues to deepen, corporate marketing activities have evolved from single-channel placements to complex systems operating across platforms, terminals, and scenarios[1,2]. Marketing technology platforms, as crucial infrastructure connecting user reach, content distribution, advertising, customer operations, and conversion management, are reshaping the entire process of acquiring traffic, identifying needs, stimulating conversions, and accumulating value. In this context, marketing decisions are no longer limited to superficial measurements of exposure or clicks, but increasingly emphasize identifying the true role of different marketing touchpoints in value creation from the perspective of user behavior. How to accurately characterize the contribution relationships of touchpoints in a multi-

source, heterogeneous, time-intertwined, and feedback-lagging marketing environment, and further achieve quantitative evaluation of return on investment, has become a key issue in the intelligent upgrading of marketing technology platforms and an important topic in data-driven marketing research[3].

Attribution modeling is a core component of marketing effectiveness analysis, aiming to explain the marginal contribution and mutual influence mechanisms of various marketing contact behaviors behind user conversion results. As the channel structure of corporate marketing activities becomes increasingly complex, traditional attribution methods relying on single paths, static rules, or simple weight allocation are no longer adequate to adapt to the dynamic changes in real business scenarios. On the one hand, user decision-making processes typically exhibit significant nonlinearity, delays, and context-dependent characteristics, with reinforcing, substituting, or phased collaborative relationships often existing between different touchpoints[4]. On the other hand, significant differences exist between platform-internal and external data in terms of collection granularity, semantic expression, and time scale, leading to real challenges in the attribution process, such as information fragmentation, noise interference, and insufficient interpretation. Therefore, constructing a novel attribution modeling framework that can adapt to complex marketing chains and balance dynamic correlations with semantic understanding capabilities has significant theoretical and practical value for improving the authenticity, precision, and operability of marketing analysis.

Benefit evaluation is a crucial bridge connecting marketing analysis and business decision-making. Its essence lies in further mapping attribution results into a measurable, comparable, and optimizable value indicator system. Currently, enterprises generally face multiple pressures in marketing practice, including increasingly tight budget constraints, greater volatility in the advertising environment, and the need for refined decomposition of growth targets. Simply relying on coarse-grained input-output ratio indicators is no longer sufficient to support high-frequency, complex, and long-term resource allocation decisions. Especially with the continuous accumulation of massive behavioral, transactional, and operational data on marketing technology platforms, the ability to uniformly characterize marketing effectiveness from multiple dimensions, including short-term conversion revenue, user lifetime value, channel synergy benefits, and long-term brand building, has become a crucial prerequisite for improving platform governance capabilities and enterprise operational efficiency. Systematic research on revenue assessment not only helps shift marketing activities from experience-driven to model-driven approaches but also enhances the platform's support capabilities for budget allocation, strategy adjustment, and risk identification.

The development of large language models provides new research opportunities for attribution modeling and revenue assessment in marketing technology platforms. Compared to traditional methods that primarily rely on structured variables for pattern learning, large language models demonstrate stronger versatility in semantic representation, knowledge transfer, contextual modeling, and adaptation to complex tasks. They are particularly suitable for handling the widespread textual information, behavioral descriptions, strategy rules, and multimodal business contexts present in marketing scenarios. By constructing targeted fine-tuning frameworks for marketing tasks, the model's ability to understand domain knowledge, business logic, and value judgment standards can be further enhanced, thereby promoting deep integration between attribution analysis, revenue estimation, and decision support. Research on attribution modeling, benefit assessment, and large language model fine-tuning frameworks around marketing technology platforms not only helps to expand the methodology in the field of intelligent marketing but also provides solid support for enterprises to achieve higher levels of refined operation, scientific evaluation, and intelligent decision-making.

2. BackGround

As enterprises deepen their digital transformation, marketing technology platforms have evolved from simple tools for campaign support into comprehensive foundational platforms integrating data collection, user identification, process automation, content collaboration, channel management, and business analysis[5]. Their core role extends beyond simply improving marketing execution efficiency; it lies in

building a continuous value chain covering user reach, interaction response, purchase conversion, and subsequent operations by integrating data resources scattered across different business segments. As the business environment shifts from a traffic-expansion-oriented approach to a value-driven approach, the goals of marketing activities have expanded from simply pursuing short-term conversions to encompassing customer retention, relationship maintenance, repeat purchase promotion, and long-term revenue growth. This change in objective structure necessitates that marketing technology platforms possess stronger data understanding, behavioral correlation, and value characterization capabilities to adapt to increasingly complex business judgment needs[6].

Simultaneously, the data types in platform-based marketing scenarios are becoming increasingly diverse, including structured behavioral records such as exposure, clicks, visits, and orders, as well as a large amount of unstructured information such as search content, interactive text, campaign plans, product descriptions, and user feedback. Traditional marketing analytics methods, when faced with multi-source heterogeneous information, often focus on local indicator statistics or single-result predictions, failing to reveal the deep connections between marketing activities, user responses, and business results as a whole[7]. Especially in the current context of enhanced channel synergy, longer user decision-making paths, and constantly changing market feedback, platforms not only need to identify the immediate impact of different marketing behaviors but also understand their transmission effects and value accumulation processes over longer periods. Therefore, conducting systematic research on attribution understanding, benefit measurement, and intelligent modeling for marketing technology platforms has become a crucial foundation for upgrading marketing analytics paradigms and enhancing platform decision-making capabilities.

3. Methodology

To address the joint problem of attribution modeling, revenue evaluation, and task-oriented large language model adaptation in a marketing technology platform, the proposed framework organizes heterogeneous user interactions, campaign signals, and business outcomes into a unified decision representation space. Rather than treating conversion analysis as a static allocation problem, the method models the evolving contribution of multiple touchpoints along the user journey, so that both temporal dependency and semantic context can be preserved during value decomposition. This paper presents the overall model architecture, as shown in Figure 1.

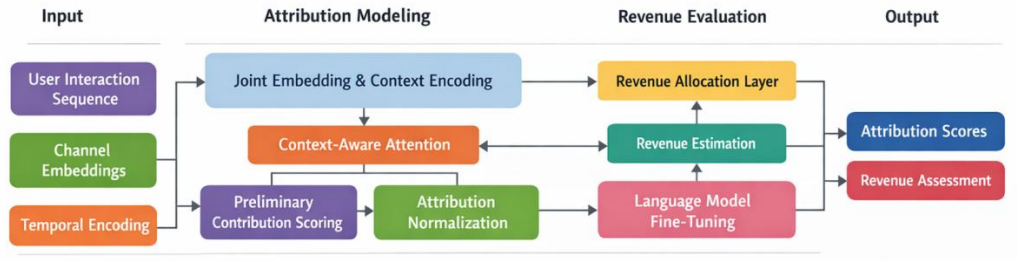


Figure 1. Overall model architecture

A user trajectory is first represented as an ordered interaction sequence:

$$S_u = \{(x_{u,1}, t_{u,1}, c_{u,1}), (x_{u,2}, t_{u,2}, c_{u,2}), \ldots, (x_{u,n}, t_{u,n}, c_{u,n})\}$$

where $x_{u,i}$ denotes the feature vector of the ith touchpoint for user u, $t_{u,i}$ denotes its occurrence time, and $c_{u,i}$ denotes the corresponding channel or campaign identifier. Since platform events usually carry both behavioral and semantic information, each touchpoint is projected into a joint embedding space through:

$$\boldsymbol{h}_{u,i} = \phi\left(\boldsymbol{W}_x x_{u,i} + \boldsymbol{W}_t \tau_{u,i} + \boldsymbol{W}_c e_{u,i}\right)$$

in which $\tau_{u,i}$ is the temporal encoding derived from $t_{u,i}$, $e_{u,i}$ is the learnable channel embedding associated with $c_{u,i}$, and $\phi(\cdot)$ is a nonlinear transformation used to enhance cross-source feature interaction. Because recent and semantically aligned events should not always dominate the attribution process in the same manner, a context-aware weighting mechanism is introduced as:

$$\alpha_{u,i} = \frac{exp\left(\boldsymbol{q}_u^{\top} \boldsymbol{K} \boldsymbol{h}_{u,i} - \lambda \Delta t_{u,i}\right)}{\sum_{j=1}^{n} exp\left(\boldsymbol{q}_u^{\top} \boldsymbol{K} \boldsymbol{h}_{u,j} - \lambda \Delta t_{u,j}\right)}$$

where $\boldsymbol{q}_u$ summarizes the current decision context of user u, $\boldsymbol{K}$ is a trainable projection matrix, $\Delta t_{u,i}$ measures the lag between the ith touchpoint and the final target event, and λ controls the rate of temporal attenuation. Guided by this design, the global trajectory representation becomes:

$$\boldsymbol{z}_u = \sum_{i=1}^{n} \alpha_{u,i} \boldsymbol{h}_{u,i}$$

which allows the framework to compress long and noisy user journeys into a compact state vector while preserving the most decision-relevant structural information for subsequent attribution and value estimation.

Structured state representation and hierarchical policy scheduling motivate organizing long, heterogeneous touchpoint paths into a controllable decision state with explicit planning levels. Graph contrastive learning for call-graph anomaly perception further supports using consistency across transformed interaction views to suppress incidental path variation while retaining contribution-relevant relational changes[8], [9]. Dynamic representation alignment in distributed data anomaly detection and deep graph learning for concealed fraud detection likewise motivate regularizing attribution embeddings against cross-context drift and emphasizing latent relations that expose subtle, coordinated deviations in enterprise interaction networks[10], [11].

Beyond trajectory compression, the method explicitly constrains attribution scores to remain interpretable under multi-touch interactions, since business deployment requires channel contribution to be comparable across campaigns, users, and time windows. Each touchpoint, therefore, receives a preliminary contribution estimate through:

$$s_{u,i} = \boldsymbol{w}_a^{\top} tanh\left(\boldsymbol{W}_h \boldsymbol{h}_{u,i} + \boldsymbol{W}_z \boldsymbol{z}_u\right)$$

where $\boldsymbol{W}_h$ and $\boldsymbol{W}_z$ fuse local event evidence and global journey context, while $\boldsymbol{w}_a$ maps the fused representation to a scalar attribution logit. To avoid unstable allocation caused by scale variation across users, a normalized attribution coefficient is further defined as:

$$\beta_{u,i} = \frac{exp\left(s_{u,i}\right)}{\sum_{j=1}^{n} exp\left(s_{u,j}\right)}$$

so that the full conversion credit of one user path is redistributed over all observed touchpoints in a probability-consistent manner. Such a formulation is important because it preserves additivity and operational transparency at the same time, making it suitable for downstream budget allocation, campaign ranking, and cross-channel coordination.

Value-iteration reinforcement learning for critical-task scheduling motivates evaluating campaign choices by their downstream value under constrained execution priorities. Adaptive replica allocation further reinforces adapting allocation decisions to resource and dependency constraints at execution time, which is consistent with assigning credit across competing marketing touchpoints[12], [13].

From the perspective of platform management, attribution alone is insufficient unless the estimated contribution can be translated into measurable economic value. For this reason, the framework introduces a revenue evaluation layer that links behavioral credit to realized or expected return. Given the observed

revenue target y_u of user u, which may refer to conversion value, expected profit, or lifetime contribution under a selected business horizon, the marginal revenue assigned to each touchpoint is computed as:

$$r_{u,i} = \beta_{u,i} \cdot y_u$$

thereby producing a direct mapping from path-level outcome to event-level value allocation. Since platform optimization usually requires coordinated learning over attribution quality, revenue sensitivity, and language-guided task understanding, the overall training objective is formulated as:

$$\mathcal{L} = \mathcal{L}_{\text{pred}} + \eta_1 \mathcal{L}_{\text{attr}} + \eta_2 \mathcal{L}_{\text{rev}} + \eta_3 \mathcal{L}_{\text{ft}}$$

Swhere $\mathcal{L}_{\text{pred}}$ supervises target prediction, $\mathcal{L}_{\text{attr}}$ regularizes attribution consistency, $\mathcal{L}_{\text{rev}}$ constrains revenue estimation fidelity, and $\mathcal{L}_{\text{ft}}$ governs domain-adaptive fine-tuning of the large language model, with η_1, η_2, and η_3 balancing the relative importance of each component. This coupled objective enables the model to align statistical estimation with business semantics, which is essential when marketing decisions must be explainable, value-aware, and adaptable to changing campaign language.

Evolutionary strategy-driven self-optimization supports policy exploration when the attribution environment changes, while adaptive multi-agent reinforcement learning for dynamic financial risk transmission motivates treating cross-channel budget and attribution feedback as coupled decisions whose coordination reduces exposure to volatile returns[14], [15].

At the semantic adaptation level, the large language model is not used as an isolated text generator but as a domain knowledge carrier that enhances the interpretation of campaign descriptions, customer intents, and platform rules embedded in non-structured marketing data. To specialize the model toward attribution-sensitive decision analysis, a parameter-efficient fine-tuning strategy is incorporated into the joint framework, allowing semantic priors to be aligned with platform-specific optimization targets while avoiding excessive parameter updates. More importantly, the semantic module provides additional context for sparse or ambiguous user actions, thereby improving the consistency between behavioral evidence and strategic business interpretation. Through this design, the proposed method forms a closed analytical chain from touchpoint representation and credit decomposition to revenue mapping and language-guided adaptation, which gives the overall framework stronger practical significance for intelligent marketing decision support, value assessment, and fine-grained attribution governance.

Task-graph construction for large language model agents motivates translating campaign instructions, operational rules, and analytical subgoals into explicit dependency-aware plans, allowing the fine-tuned model to preserve coherent semantic reasoning through attribution and revenue-evaluation workflows[16].

4. Experimental Results and Analysis

4.1 Dataset

This paper uses the Criteo Attribution Modeling for Bidding Dataset as the research dataset. This dataset consists of publicly available advertising traffic logs, derived from anonymized samples of 30 days of real online marketing scenarios. Each record corresponds to one ad display event and provides key information related to the context, click behavior, conversion results, and whether the data is attributed to the platform. Therefore, it can effectively cover the core data elements required for multi-touchpoint attribution modeling, conversion value identification, and revenue assessment in marketing technology platforms. Because this dataset includes user interaction sequences, channel contact signals, time-related information, and conversion tags, it is suitable for building attribution analysis models for the marketing chain and can also provide foundational support for revenue estimation and fine-tuning of large language models for marketing semantic tasks. Furthermore, this dataset is publicly released and provides standardized access methods, exhibiting good accessibility, reproducibility, and research suitability.

In this study, AUC, F1, MAE, and RMSE are adopted as evaluation metrics because they jointly reflect the effectiveness of the proposed framework from both classification and estimation perspectives, which is consistent with the dual objectives of attribution modeling and revenue assessment. Specifically, AUC is used to measure the overall discriminative ability of the model under different decision thresholds, making it suitable for evaluating whether the framework can effectively distinguish conversion-related and non-conversion-related marketing interactions in complex multi-touch environments. F1 is introduced to provide a balanced assessment of precision and recall, which is particularly important in marketing datasets where positive conversion events are often relatively sparse and a single accuracy-oriented metric may fail to capture the true predictive quality. Meanwhile, MAE and RMSE are employed to evaluate the error between predicted and actual value-related targets, since the proposed method not only needs to identify attribution patterns but also needs to estimate revenue-related outcomes with sufficient numerical reliability. Among them, MAE reflects the average magnitude of prediction deviation in a direct and interpretable manner, while RMSE places greater emphasis on larger errors and is therefore useful for assessing the stability and robustness of the framework in value estimation tasks. The combined use of these four metrics enables a more comprehensive evaluation of the model performance and provides a more appropriate assessment basis for the integrated task setting of marketing attribution analysis and revenue-oriented decision modeling.

4.2 Experimental setup

To ensure the research on attribution modeling, benefit assessment, and a large language model fine-tuning framework for marketing technology platforms has good training stability and reproducibility, the experimental phase standardized the data preprocessing strategy, model training process, and core parameter configuration. Specifically, the original marketing behavior data was first deduplicated, missing values were removed, time fields were standardized, and category features were encoded to ensure the temporal consistency of multi-touchpoint interaction sequences. Then, training, validation, and test sets were constructed according to a unified data partitioning scheme, and the attribution modeling, benefit assessment, and large language model fine-tuning modules were jointly trained under the same input specifications. Considering that marketing scenarios contain both structured behavioral features and unstructured semantic information, the text semantic modeling part uses Qwen7B as the basic large language model to enhance the understanding of marketing context, touchpoint semantic relationships, and benefit-related information. Meanwhile, parameters such as optimizer, learning rate, batch size, maximum sequence length, and number of training epochs were all configured uniformly to reduce training bias between different modules and improve the overall framework consistency. The main hardware and software environment and key parameter settings used in this experiment are shown in Table 1.

Table 1. Main Experimental Hyperparameter Settings

Category	Configuration Item	Setting
Hardware Environment	GPU	NVIDIA A100 80GB
Hardware Environment	CPU	Intel Xeon server-grade processor
Hardware Environment	Memory	128 GB
Software Environment	Operating System	Linux
Software Environment	Deep Learning Framework	PyTorch
Software Environment	Python Version	Python 3.10
Language Model Configuration	Base Large Language Model	Qwen7B

Data Processing	Data Split Ratio	Training set : Validation set : Test set = 8 : 1 : 1
Data Processing	Missing Value Handling	Removal of incomplete samples and standardized completion for selected fields
Data Processing	Categorical Feature Processing	Embedding encoding
Data Processing	Temporal Feature Processing	Timestamp standardization and temporal encoding
Training Parameters	Batch Size	16
Training Parameters	Initial Learning Rate	1e-4
Training Parameters	Optimizer	AdamW
Training Parameters	Weight Decay	1e-5
Training Parameters	Number of Epochs	50
Training Parameters	Maximum Sequence Length	128
Training Parameters	Random Seed	42

4.3 Experimental Results and Analysis

To systematically present the methodological positioning of the proposed framework in marketing attribution modeling, revenue assessment, and semantic enhancement analysis scenarios, this paper selects seven representative studies closely related to multi-touchpoint attribution, online advertising attribution, path-level credit allocation, and marketing value optimization as comparison objects, and organizes them uniformly from two dimensions: classification discrimination ability and revenue error control. The relevant comparisons are shown in Table 2.

Table 2. Comparative results of related methods and the proposed method

Method	**AUC**	**F1**	**MAE**	**RMSE**
Shao et al.[17]	0.84	0.78	0.24	0.38
Zhang et al.[18]	0.86	0.80	0.22	0.35
Diemert et al.[19]	0.87	0.81	0.21	0.33
Ji et al.[20]	0.88	0.82	0.19	0.31
Ren et al.[21]	0.85	0.79	0.23	0.36
Du et al.[22]	0.89	0.83	0.18	0.29
Yao et al.[23]	0.90	0.84	0.17	0.27
Ours	**0.93**	**0.88**	**0.13**	**0.21**

The proposed method exhibits the best overall performance, demonstrating its ability to more effectively characterize the intrinsic relationship between multi-touchpoint interaction behaviors and revenue information within marketing technology platforms. Furthermore, it demonstrates stronger discriminative ability, fitting ability, and stability in attribution modeling and value assessment tasks. This indicates that the constructed unified framework not only improves the accuracy of identifying the contribution relationships of key marketing touchpoints but also more accurately characterizes and predicts revenue-related information. This is because the proposed method considers the contextual dependence of user interaction sequences, the synergistic effect of channel information, the dynamic influence of time factors, and the enhancement effect of large language models in marketing semantic understanding during the modeling process. This enables the model to learn more complete and business-meaning representation features in complex marketing scenarios, further validating the effectiveness and application value of the proposed method in intelligent marketing analysis tasks.

To further verify the actual contribution of each key component to the overall framework performance, this paper conducts ablation analysis on the core modeling steps of the method, removing the context-aware attention mechanism, the attribution normalization module, and the large language model fine-tuning module, and evaluates the model performance under unified settings. The relevant results are shown in Table 3.

Table 3. Ablation results of different module settings and the complete framework

Ablation Setting	AUC	F1	MAE	RMSE
w/o Context-Aware Attention	0.89	0.84	0.18	0.28
w/o Attribution Normalization	0.90	0.85	0.17	0.26
w/o Language Model Fine-Tuning	0.91	0.86	0.16	0.25
Ours	**0.93**	**0.88**	**0.13**	**0.21**

As shown in Table 3, the proposed complete framework achieves optimal performance, indicating that each key component plays an irreplaceable role in the overall modeling process. Specifically, the context-aware attention mechanism enhances the model's ability to capture multi-touchpoint interaction relationships and temporal dependency information, making the attribution process more consistent with the dynamic characteristics of real marketing chains. The attribution normalization module further improves the rationality and consistency of touchpoint contribution allocation, thus ensuring better stability and interpretability of the revenue mapping process. The large language model fine-tuning module strengthens the model's understanding of marketing semantic information, user behavior context, and platform task rules, making the overall representation more complete and business-relevant. Therefore, the proposed method effectively improves the overall performance of attribution modeling and revenue evaluation tasks through the collaborative modeling of behavioral information, attribution relationships, and semantic knowledge, further demonstrating the strong effectiveness and application value of the proposed framework.

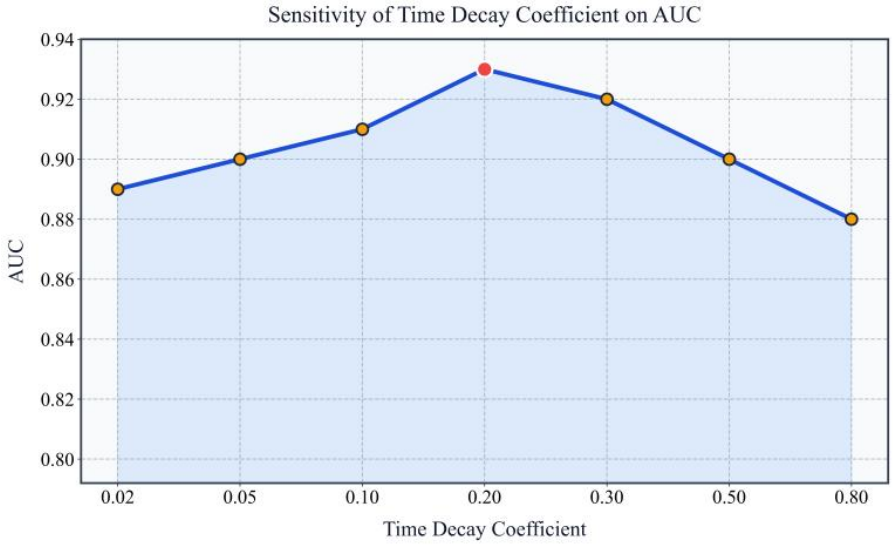


Figure 2. Time decay factor on AUC

The results presented in Figure 2 show that the time decay coefficient has a significant impact on model performance. A moderate parameter setting can more effectively balance the contribution relationship between early touchpoint information and later key behaviors, thereby improving the overall attribution model's discriminative ability. When this parameter is set too small, the model retains more influence from earlier marketing touchpoints, easily weakening the identification role of key near-conversion behaviors in the decision-making chain. Conversely, when this parameter is further increased, excessive time decay compresses the effective expression of preceding behavioral information, making it difficult to fully utilize long-term dependencies in the user's complete interaction path. This indicates that in the context of marketing technology platforms, a reasonable time decay mechanism can more accurately characterize the dynamic characteristics of user touchpoint contributions changing over time and provide more stable temporal support for attribution modeling and revenue evaluation.

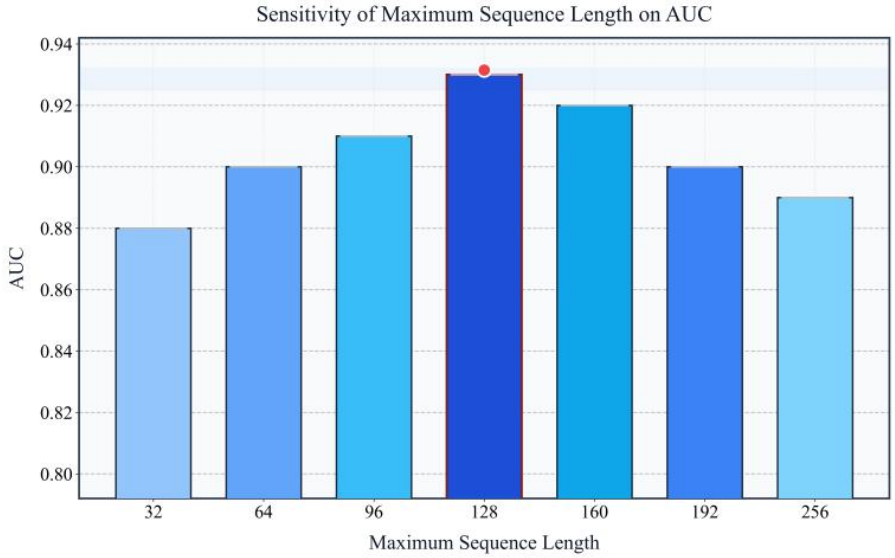


Figure 3. The effect of maximum sequence length sensitivity on AUC

The setting of the maximum sequence length directly affects the model's coverage of the user behavior chain and its information filtering effectiveness, as shown in Figure 3. A shorter sequence length can easily lead to premature truncation of some preceding marketing contact information, making it difficult for the model to fully understand the complete decision-making process. While a continuously expanding sequence range

can incorporate more historical behaviors, it also introduces redundant information with weak relevance to the final conversion, thus weakening the ability to focus on key touchpoint signals. Therefore, the method presented in this paper, with an appropriate sequence length, can better balance path integrity and effective information condensation, maintaining a more coordinated modeling relationship between user interaction representation, attribution weight learning, and subsequent benefit characterization, thereby demonstrating stronger overall adaptability.

5. Conclusion

This paper addresses the collaborative challenges of attribution modeling, benefit assessment, and fine-tuning of large language models within marketing technology platform scenarios. It constructs a unified analytical framework for multi-touchpoint user behavior chains. To resolve issues with traditional marketing analysis methods in complex channel environments, such as insufficient attribution granularity, simplistic benefit characterization, and limited semantic understanding, this paper systematically designs multiple layers, including user interaction sequence representation, touchpoint contribution allocation, benefit mapping mechanisms, and domain semantic modeling. This integrates attribution analysis and value assessment within a unified modeling space, preventing them from becoming isolated processes. This research not only deepens the understanding of marketing behavior pathways but also provides a clearer methodological path for the evolution of marketing technology platforms from process support tools to intelligent decision-making infrastructure.

From the research content, the proposed method is well-suited to the realities of marketing technology platforms, characterized by the coexistence of multi-source heterogeneous information, complex and intertwined touchpoint relationships, and multi-dimensional coupling of business objectives. On one hand, by jointly modeling user temporal interaction information, channel contact signals, and contextual semantic information, the framework can more accurately identify the actual roles of different touchpoints in the marketing chain, thereby enhancing the rationality of attribution results and their business interpretability. On the other hand, the revenue assessment module further links attribution results with value objectives, enabling the model to not only answer which touchpoints had an effect, but also how these effects map to the operational value the platform focuses on. This integrated modeling approach, from behavioral understanding to value quantification, helps overcome the problems of previous marketing analysis that emphasized identification over interpretation and prediction over decision-making, providing a more reliable analytical basis for refined marketing management.

At the application level, this research has strong practical significance for fields such as digital marketing, advertising optimization, customer relationship management, budget allocation, and intelligent operational decision-making. As enterprise marketing activities gradually develop towards omnichannel collaboration, full user lifecycle operation, and data-driven decision-making, the role of marketing technology platforms has expanded from simple information integration and process execution to core support for operational insights and resource allocation. The research framework proposed in this paper can provide platforms with more granular touchpoint value identification capabilities, more stable revenue assessment capabilities, and stronger marketing semantic understanding capabilities, thereby helping enterprises more accurately identify high-value marketing paths, optimize resource allocation efficiency, and improve overall operational quality. Furthermore, this research provides a feasible approach for the task-oriented implementation of large language models in marketing analytics, promoting their expansion from general semantic generation capabilities to specialized modeling capabilities for business decision-making. This has positive implications for the in-depth development of intelligent marketing systems.

Future research can be further deepened in several directions. First, by combining longer-term user lifecycle data, cross-platform behavioral data, and richer business feedback signals, the model's ability to characterize long-term value creation processes can be further enhanced, making attribution analysis closer to the

continuous cumulative characteristics in real-world business scenarios. Second, more flexible online updating and adaptive modeling methods can be explored, focusing on dynamic environmental changes, strategy adjustments, and real-time feedback mechanisms within marketing technology platforms, to enhance the framework's continuous adaptability to rapidly changing market conditions. Third, the collaborative methods between large language models and structured behavioral analysis can be further expanded, enabling the model not only to understand marketing texts and business rules but also to participate more deeply in strategy generation, value interpretation, and decision support processes. With the deepening of intelligent marketing, platform governance, and enterprise digital operation, research on attribution modeling, benefit assessment, and semantic enhancement decision-making will have a broader development space. The work in this paper can also provide a certain reference basis for related theoretical research and industrial practice.

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