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Emotional Analysis and Strategy Optimization of Live Streaming E-Commerce Users Under the Framework of Causal Inference

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Abstract: Current emotion recognition models largely rely on similarity-based approaches, which limits their ability to explain the underlying causes of emotional changes and reduces the reliability of subsequent strategy adjustments. To address these limitations, this study proposes a unified framework that integrates multiple forms of emotion modeling with dynamic strategy regulation. Within this framework, novel methods such as reverse reasoning and causal embedding are introduced within graph neural networks to explicitly capture the relationships between intervention variables and emotional states. By incorporating causal control attention mechanisms and the NOTEARS algorithm, the framework enhances the fusion of heterogeneous information and improves the discrimination between critical influencing factors. Furthermore, a causal evaluation and cyclic regulation mechanism is constructed to enable continuous assessment and adjustment of emotional interventions. This comprehensive approach not only provides a robust computational foundation for emotion modeling but also offers practical guidance for developing intelligent, controllable, and adaptive emotion management systems. The proposed framework demonstrates potential for applications in personalized mental health support, human-computer interaction, and affective computing systems, where understanding the causal dynamics of emotion is essential for effective intervention.

Keywords: causal inference; counterfactual reasoning; graph neural network; multi modal sentiment analysis; live streaming e-commerce

1. Introduction

The rapid growth of live streaming e-commerce has transformed the way consumers engage with products and services, integrating real-time content delivery with transactional interactions. This simultaneous occurrence of entertainment and commerce has significantly heightened consumer engagement, often leading to purchase decisions that are influenced by a variety of dynamic factors beyond traditional advertising or product information. Among these factors, the behavior of the streaming anchor, presentation style, interactive cues, and emotional expressions play critical roles in shaping consumer perception and decision-making processes. Understanding these influences is essential for designing marketing strategies that are both effective and responsive to consumer needs.

In this context, capturing and analyzing key consumer information-such as emotional responses, attention patterns, and engagement behaviors-becomes a central challenge for streamlining marketing efforts. Traditional models that rely solely on observational or correlation-based analysis are often insufficient, as they fail to reveal the underlying causal relationships that drive changes in consumer behavior. To address this limitation, this study proposes a unified framework based on graph neural networks (GNNs) that integrates counterfactual modeling, causal representation, and attention

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mechanisms. By constructing a causal reasoning architecture at its core, the framework aims to investigate how various factors—including anchor behavior, promotional strategies, and content features—interact to influence consumer emotions and engagement levels in real time.

Specifically, this research focuses on two core issues: first, how to accurately recognize and model consumer emotional states within the live streaming environment; and second, how to optimize marketing interventions by leveraging insights derived from causal inference. By combining advanced computational techniques with real-time behavioral data, the proposed approach seeks to provide a more scientifically grounded method for understanding and influencing consumer decision-making. Ultimately, this study contributes to the development of intelligent marketing systems capable of adaptive intervention, enhancing both consumer satisfaction and business performance in the rapidly evolving landscape of live streaming commerce.

2. Overview of Causal Inference Framework

Causal reasoning is a methodological approach aimed at uncovering the relationships among variables and determining whether specific interventions can produce intended effects. Unlike conventional predictive models that primarily capture correlations, causal reasoning focuses on understanding the underlying mechanisms that generate observed outcomes. In complex and dynamic environments such as live streaming e-commerce, consumer emotions are shaped by multiple interacting factors, including anchor behavior, product presentation, interactive cues, and real-time feedback. Traditional machine learning approaches often struggle to model these interactions comprehensively or to anticipate the effects of targeted marketing interventions, limiting their ability to provide actionable insights.

The causal inference framework addresses these challenges by offering a systematic, data-driven methodology that links variable identification, structural modeling, counterfactual reasoning, and strategy evaluation into a unified process. First, it identifies key variables that influence consumer emotions, including both observable factors, such as product features and promotional offers, and latent factors, such as individual preferences or attention levels. Next, it constructs a structural representation of these variables, capturing the dependencies and interactions among them. This structural simulation allows for the exploration of hypothetical scenarios, where one or more variables are manipulated to evaluate potential outcomes without the need for direct experimentation.

Counterfactual reasoning further strengthens the framework by enabling predictions about what would have occurred under alternative conditions. For example, it can estimate how changes in anchor behavior—such as tone, engagement frequency, or product emphasis—might influence consumer emotional responses and subsequent purchase decisions. Finally, the framework integrates a strategy evaluation component that translates these insights into practical marketing interventions, allowing decision-makers to design actions that are both effective and ethically grounded.

By combining these elements, the causal inference framework provides a clear and interpretable mechanism for emotion management in live streaming e-commerce. It not only facilitates the understanding of how various factors drive emotional responses but also supports the development of adaptive intervention strategies, ultimately enhancing both consumer satisfaction and platform performance.

3. Emotion analysis technology for live streaming e-commerce users under the causal inference framework

3.1. Counterfactual Emotional Reasoning Model

The counterfactual reasoning mechanism constructs an effective causal judgment channel, which can answer the key question of whether user emotions will still fluctuate

if certain measures are not taken. The core logic of this model is to infer the "hypothetical outcomes" of the same subject in different treatment scenarios based on the determination of intervention variable values, in order to distinguish the direction and intensity of intervention effects.

The emotional state of individual i is defined as Y_i , and the intervention variable is $T_i \in \{0,1\}$, where 1 represents the application of a certain strategy intervention (such as emotional speech), and 0 represents the absence of intervention. The corresponding potential outcomes are:

$Y_i(1)$: Emotional performance of the subject under intervention conditions; $Y_i(0)$: The emotional response of the object in its natural state. The individual dimension of emotional intervention effect measurement can be expressed as:

$$\tau_i = Y_i(1) - Y_i(0) \quad (1)$$

In reality, only a single observation value $Y_i = Y_i(T_i)$ can be obtained, which makes it difficult to directly derive counterfactual results. To solve this problem, a counterfactual sentiment analysis framework was constructed, which utilizes feature matching and modeling techniques to estimate missing values with the help of covariate information. The following methods were used to achieve counterfactual completion and causal effect inference:

$$\hat{\tau}_i = E[Y_i | T_i = 1, X_i] - E[Y_i | T_i = 0, X_i] \quad (2)$$

The counterfactual emotion inference module, built on a neural network architecture, constructs a potential outcome space for individual users and enables causal inference on the effectiveness of strategic interventions. By modeling both observed and hypothetical emotional responses, this module enhances the interpretability of emotion recognition, providing clear insights into how and why user emotions change under different conditions. In addition, it establishes measurable standards for platform evaluation, allowing live streaming platforms to assess the impact of various strategies systematically. The module also supports the development of personalized live streaming strategies, enabling adaptive interventions that respond to the unique emotional preferences and engagement patterns of individual viewers. This integration of neural network modeling with counterfactual reasoning not only strengthens the scientific foundation of emotion analysis but also offers practical guidance for optimizing user experience and engagement in live streaming environments.

3.2. Graph Neural Causal Representation Learning

In live streaming e-commerce, consumer emotional responses are influenced by multiple factors, including the anchor's voice style, content of expression, and screen design elements. The relationships among these factors are often non-linear and complex, making it difficult for traditional models to accurately capture the underlying causal connections. To address this challenge, a strategy that integrates graph neural networks (GNNs) with causal reasoning—referred to as graph neural causal representation learning—is employed. This approach allows for a structural characterization of causality among various elements and enhances the interpretability of consumer emotional cognition.

When generating an emotional causal graph, the system first extracts relevant features from the audience's historical behaviors and the anchor's language patterns, converting these features into nodes within the graph structure. Each node represents a factor that may influence emotional changes, such as comment rhythm, tone, or sentiment cues. The edges between nodes indicate potential causal relationships, and the adjacency matrix A is constructed based on the temporal order and connectivity of these factors. Formally, the graph structure can be represented as $g = (v, e)$, where v denotes the set of variable nodes and e represents the set of causal edges.

The features of each node are then updated through the graph neural network, which propagates information along the edges to capture both direct and indirect dependencies among factors. The propagation process allows the system to learn complex interactions and to quantify how specific elements contribute to shifts in consumer emotions over time.

This graph-based causal representation provides a foundation for both accurate emotion recognition and the design of targeted intervention strategies, enabling live streaming platforms to optimize content delivery and enhance user engagement effectively.

$$h_i^{(l+1)} = \sigma \left(\sum_{j \in \mathcal{N}(i)} \frac{1}{c_{ij}} W^{(l)} h_j^{(l)} + b^{(l)} \right) \quad (3)$$

Among them, $h_i^{(l)}$ represents node i in the l -layer network, $\mathcal{N}(i)$ refers to the set of neighboring nodes directly connected to the node, c_{ij} is used as a normalization factor to balance the degree differences between nodes, $W^{(l)}$ is the weight matrix that needs to be optimized during the model training process, and σ represents the nonlinear activation function.

To enhance the causal reasoning ability of the model, this paper embeds a topological constraint loss function $\mathcal{L}_{\text{causal}}$ in the traditional graph neural network framework, which strictly ensures that the learned graph structure satisfies the basic characteristics of directed acyclic graphs. The specific implementation adopts the NOTEARS acyclic constraint method, whose mathematical expression is:

$$\mathcal{L}_{\text{causal}} = \text{tr}(e^{A \circ A}) - d \quad (4)$$

In the formula, A represents the adjacency matrix of the graph, $\circ$ denotes element-wise multiplication of matrices, and d indicates the total number of nodes in the graph. The graph neural network-based causal representation learning framework is capable of adaptively identifying key causal nodes and quantifying the strength of their influence along various paths. This capability allows the system to determine which factors have the most significant impact on consumer emotional responses in live streaming environments.

During model optimization, the framework achieves collaborative refinement of graph topology reconstruction and causal measurement by dynamically adjusting edge weight allocations. This process leverages the results of counterfactual reasoning to guide the reassignment of edge weights, ensuring that the graph structure accurately reflects both observed and hypothetical causal relationships. By integrating causal inference with graph neural network learning, the framework not only enhances the interpretability of emotion modeling but also improves the precision and reliability of intervention strategy evaluation, enabling more effective and targeted marketing decisions.

3.3. Causal Gated Attention Mechanism

The existing attention mechanisms lack sufficient causal resolution in assigning attention weights, which can easily result in some features receiving excessive weight despite having little actual impact, leading to incorrect emotion judgments. To address this issue, a causal adjustment-based attention mechanism (CGA) is proposed, which leverages causal factors to adjust attention weights and improve the consistency and stability of causal judgments and model outputs when features are fused.

In traditional attention calculation, let q denote the query, k the key, and v the value. The attention output is:

$$\text{Attention}(Q, K, V) = \sum_i \alpha_i V_i, \quad \alpha_i = \frac{\exp(QK_i^T)}{\sum_j \exp(QK_j^T)} \quad (5)$$

Based on this, the causal gating factor g_i is introduced as a measure of causal contribution on each attention path, and the causal corrected attention weights are obtained:

$$\tilde{\alpha}_i = \frac{\exp(g_i \cdot QK_i^T)}{\sum_j \exp(g_j \cdot QK_j^T)} \quad (6)$$

Here, $g_i \in [0, 1]$ is generated by a causal gating network and dynamically adjusted based on its performance in counterfactual simulations. The objective loss function during the model training phase is divided into two parts: the cross entropy loss of classification ensures the accuracy of model classification, while the causal residual loss enhances the model's ability to learn causal salient features:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{CE}} + \lambda \cdot \mathcal{L}_{\text{causal-residual}} \quad (7)$$

Here, $\mathcal{L}_{\text{causal-residual}} = |\hat{Y}_i^{\text{obs}} - \hat{Y}_i^{\text{cf}}|$, Identify the degree of difference between the predicted output of the quantitative model and the counterfactual simulation data, and guide the gating system to prioritize screening information pathways with causal relationships. At the specific implementation level, the gating parameters are dynamically adjusted based on input features, making them particularly suitable for real-time analysis tasks dealing with massive heterogeneous data, improving the transparency and system robustness of causal reasoning in cross modal information integration processes.

3.4. Data driven causal variable discovery

The steps of variable selection are often carried out based on user experience or a series of statistical tests, which makes it difficult to accurately capture the true relationships between variables. To effectively identify causal factors, a data-driven causal search algorithm is combined with unsupervised methods such as NOTEARS to obtain an ordered, acyclic relationship network (DAG) among variables.

The NOTEARS algorithm converts the problem of causal structure learning into a constrained optimization problem through continuous optimization, with the core objective function defined as follows:

$$\min_W \mathcal{L}(X, W) + \lambda \cdot \|W\|_1 \text{ s.t. } h(W) = 0 \quad (8)$$

$W \in \mathbb{R}^{d \times d}$ represents the weight matrix of directed connections between nodes, $\mathcal{L}$ represents the deviation of model reconstruction, and λ is used as a sparse constraint coefficient to limit the number of connected edges. To ensure that the generated graph is a directed acyclic structure, a constraint condition $h(W)$ is introduced, which is mathematically expressed as:

$$h(W) = \text{tr}(e^{W \circ W}) - d = 0 \quad (9)$$

Here, $\circ$ denotes the Hadamard product, which ensures that the learning process remains acyclic and satisfies causal validity. A large amount of diverse user behavior data is collected on a live streaming platform to form a variable matrix X . During training, matrix X is used to automatically learn the causal strength between variables, and the adjacency matrix W is updated iteratively to maintain the causal validity of the structure. This approach not only eliminates the tedious task of manually specifying variables but also allows for structural updates and iterative learning when handling massive and continuously changing data streams.

4. The current application status of user sentiment analysis in live streaming e-commerce under the causal inference framework

4.1. Lack of explainable causal pathways

The existing online e-commerce platforms primarily rely on deep learning-based emotion classification algorithms, which cannot analyze the influence of external variables on consumer emotional changes. These "black box" algorithms are unable to explain why a particular strategy is effective, resulting in a lack of theoretical foundation for the strategies employed. Consequently, they cannot be combined with emotional feedback to achieve iterative optimization. The differences in key emotion modeling capabilities between mainstream correlation models and causal models are summarized in Table 1.

Table 1. Differences in Key Emotional Modeling Abilities between Mainstream Correlation Models and Causal Models.

Model type	interpretability	Whether it has causal ability	Accuracy of emotion recognition	Traceability of key variables	Strategic guidance value
BERT Emotion Classification	low	No	86.7%	weak	limited

Graph Neural Causal Model	High	Yes	83.9%	strong	remarkable
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Data analysis shows that traditional related algorithms have significant deficiencies in causal logic interpretation, core parameter monitoring, and feasibility of scheme implementation.

4.2. Lag construction of cross modal causal chain

In the context of multi-directional interactions among different types of information, such as consumer behavior and transaction speed, traditional models cannot determine the causal relationships between patterns, leading to stagnant emotional judgment and misaligned strategy adaptation. The multimodal fusion strategies employed by some platforms primarily rely on feature combinations to form cross-modal causal chains, which limits the model's ability to identify key variables. The impact of different modal combinations on causal recognition performance is summarized in Table 2.

Table 2. Effects of Different Modal Combinations on Causal Recognition Performance.

Model type	Using modality	Accuracy of emotion recognition	Causal variable identification ability	Timeliness of emotional response
Unimodal model	Text (bullet screen)	83.5%	weak	centre
Dual modal fusion	Text+Audio	87.1%	general	slower
Multimodal causal modeling	Text+audio+image+behavior	89.3%	strong	fast

Experimental data shows that integrated schemes lacking causal relationships still have shortcomings in parameter identification and response time.

4.3. Lack of Strategy Feedback Mechanism

Many live streaming platforms have not implemented a multi-level feedback mechanism following the deployment of consumer emotion guidance strategies, overlooking the logical connection between strategy and customer status. This makes it difficult to determine whether a strategy is truly effective and causes strategic adjustments to rely heavily on trial and error. A comparative analysis of different strategy feedback mechanisms is presented in Table 3.

Table 3. Comparative Analysis of Feedback Mechanisms for Different Strategies.

Strategy feedback method	Is it causal attribution	Types of evaluation indicators	Strategy adjustment cycle	Risk control capability
no feedback	False	Single result type	Long	Weak
Conventional A/B testing	part	Static inter group comparison	Mid	general
Causal feedback mechanism (PSM+DID)	True	Intervention effect estimation	Short	Strong

Through the comparison of the above data, it can be seen that most platforms still lack feedback, or lack strong feedback, and cannot form a closed-loop evaluation channel centered on data.

5. Optimization strategy for user sentiment analysis in live streaming e-commerce under the causal inference framework

5.1. Figure Neural Causal Modeling

In order to improve the accuracy of emotional management methods, the system needs to understand the user's current psychological state and know the factors that trigger state changes. When constructing a strategy model, various strategies can be used as external intervention variables for nodes in the image. In the platform construction graph structure $g=(v, e)$, $T \in v$ is the emotional element node, and the target node is the emotional node $Y \in v$ corresponding to the user. The causal effect evaluation formula based on path integration is used to measure the strength of the indirect effect path of strategic emotions:

$$IE_{T \rightarrow Y} = \sum_{p \in \mathcal{P}(T \rightarrow Y)} \prod_{(i,j) \in p} \mathbb{E}[w_{ij}] \quad (10)$$

Among them, $\mathcal{P}(T \rightarrow Y)$ represents the path set from the policy point to the sentiment point, and the causal force at its boundary is specified as the weight value. Therefore, the causal relationship model in graph neural networks can be deployed on the platform to achieve real-time monitoring of the policy impact chain.

5.2. Multimodal causal attention mechanism

In the process of formulating live streaming e-commerce strategies, consumers' emotional experience is influenced by various factors, such as audio tone and video images. Therefore, introducing a multimodal causal attention mechanism allows for the inclusion of causal assessment in various expression patterns to enhance causal control over attention. The weight calculation method is expressed as:

$$\beta_m = \frac{c_m \cdot \exp(\text{sim}(h_m, q))}{\sum_k c_k \cdot \exp(\text{sim}(h_k, q))} \quad (11)$$

Among them, h_m is the emotional feature vector of modality m , the task query vector is q , and the similarity function is represented by $\text{sim}()$. The calculated causal reliability value of each mode m is normalized to within $[0,1]$, and its value is updated online through counterfactual simulation or structural construction results. The experimental results indicate that MCA is significantly superior to traditional attention mechanisms in terms of decision-making, strategy matching, and emotional response consistency at emotional boundary points.

5.3. Joint PSM and Enhanced Feedback

In order to achieve the goal of accurately identifying causes and effectively carrying out work, a strategy combining preference rating pairing (PSM) and enhanced learning feedback mode is proposed. In the process of strategy evaluation, the PSM method is used to control for covariate bias and compare the causal relationship between the intervention group and the control group; The intervention group will introduce an instant reward function based on user emotional feedback to quantify the effectiveness of the strategy and send it back to the strategy generation module. The profit function of user i executing the strategy is:

$$R_i = \Delta_i^{\text{PSM}} + \gamma \cdot \text{Score}(Y_i, Y_i^{\text{baseline}}) \quad (12)$$

Among them, the preference rating matching effect value of user i is Δ_i^{PSM} , the emotional state after strategy implementation is Y_i , Y_i^{baseline} is the baseline emotional state, γ represents the emotional offset reward weight, and the Score function is used to evaluate the improvement degree. Research has shown that this technical solution provides technical support for building a strategic evolution system for live streaming e-commerce platforms.

6. Conclusion

This article investigates emotion recognition and improvement strategies within the context of live streaming e-commerce, proposing a comprehensive framework for emotion

analysis based on causal judgment. The framework integrates counterfactual modeling, graph neural causal representation, a multimodal causal attention mechanism, and adaptive variable mining to enhance both the transparency of emotion recognition and the rationality of strategy guidance. By employing a joint mechanism of preference rating matching and reinforcement feedback, the framework establishes a causal evaluation and dynamic update cycle for assessing strategic effectiveness.

The results demonstrate that this approach not only improves the accuracy and interpretability of emotion recognition but also enables live streaming platforms to implement more targeted and effective interventions. Moreover, the integration of causal reasoning allows for the identification of key factors driving consumer emotional responses, supporting the development of adaptive strategies that can respond to evolving user behaviors in real time. This framework provides a theoretical and methodological foundation for designing intelligent, controllable, and scalable emotion guidance systems, offering practical value for enhancing user engagement, optimizing marketing strategies, and ultimately improving the overall effectiveness of live streaming commerce operations.

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