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Article

Personalized Generation and Effect Evaluation of Creative Writing of Marketing Communication Driven by Affective Computing

Shengdao Shu [1,*]

[1] King's College London, London, The United Kingdom of Great Britain and Northern Ireland
[*] Correspondence: Shengdao Shu, King's College London, London, The United Kingdom of Great Britain and Northern Ireland

Abstract: In the digital age, traditional marketing communication increasingly struggles to address heterogeneous and rapidly changing individual needs. Affective computing provides new technical means for understanding and responding to user emotions, thereby enabling more precise and engaging creative writing in marketing contexts. This paper investigates the personalized generation and systematic effect evaluation of marketing communication texts driven by affective computing. First, a closed-loop framework is constructed that integrates multi-source emotional data collection, user emotional demand modeling, hierarchical content generation based on natural language generation techniques, and multi-channel emotional adaptation. Within this framework, emotional signals from diverse data sources are fused to build user profiles that guide the tailoring of tone, style, and narrative strategies in creative writing. Second, an evaluation model is proposed along the dimensions of emotion, behavior, and cognition to assess the effectiveness of generated content, including emotional resonance, engagement, and persuasive impact. Feedback from these indicators is used to iteratively optimize both the affective models and the generation strategies, forming an intelligent optimization loop. Furthermore, the study discusses key challenges such as data privacy, algorithmic bias, and content homogenization, and emphasizes the need for transparency and user consent in emotional data processing. Finally, it outlines future directions in multimodal fusion, human–machine collaboration, and intelligent evaluation mechanisms, aiming to provide theoretical and methodological support for enhancing the emotional impact, personalization, and accuracy of marketing communication content.

Keywords: affective computing; marketing; creative writing; personalization; evaluation; natural language generation

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1. Introduction

1.1. Research Background

In today's digital age, the information landscape for consumers is becoming increasingly complex, and traditional marketing communication methods can no longer meet the growing demand for personalization and interactivity. Affective computing is a cutting-edge technology that has emerged in recent years, enabling the optimization of interactions between humans and machines by identifying and analyzing human emotional states. This technology has introduced new opportunities for marketing communication, allowing creative writing to move beyond static expressions and dynamically adapt to users' emotional and cognitive needs, thereby enhancing communication effectiveness. As market competition intensifies, enterprises urgently need to leverage refined and personalized content to boost user engagement and brand loyalty. The application of affective computing enables creative writing to more accurately target audiences and provide tailored experiences [1, 2]. Simultaneously, it optimizes the allocation and utilization of marketing resources. However, it also presents a challenge to practitioners: how to efficiently collect emotional data, accurately analyze consumers' emotional needs, and transform these insights into creative content. With the continuous advancement of technology, marketing communication methods are becoming increasingly diverse, encompassing social media, mobile applications, and virtual reality. This requires enterprises to adapt their content across multiple channels to maximize its impact. Research on the personalized generation and evaluation of creative writing in marketing communication, driven by affective computing, offers an innovative approach for enterprises to enhance market competitiveness and provide consumers with more engaging experiences.

1.2. Core Concepts

1.2.1. Affective Computing

Affective computing refers to the technology of computer recognition, interpretation, processing, and simulation of human emotions. With the assistance of sensors, machine learning, and natural language processing, affective computing can analyze text, voice, facial expressions, and physiological signals to identify human emotional states. This technology aims to enhance the human-computer interaction experience and facilitate intelligent responses from computing devices to users' emotional changes. In the field of marketing, affective computing enables enterprises to capture consumers' emotional cues, transform data into actionable insights, and provide support for precision marketing and personalized content. Its application not only improves the emotional connection between the brand and the audience but also enhances the user's sense of participation and loyalty, providing a new way to refine and differentiate market strategies.

1.2.2. Marketing Creative Writing

Marketing creative writing is a content creation process that attracts and influences the attention and emotion of the target audience through innovative language style and expression techniques. It aims to convey brand value and product information through storytelling, slogan design, and advertising copy. Effective marketing creative writing is not only original and unique in form but also accurately captures consumers' needs and psychological resonance in its content while promoting brand communication and product promotion. As the digital landscape evolves rapidly, marketing creative writing must adapt more swiftly to market changes. It should leverage technologies like affective computing to create contextualized and personalized content that addresses the needs of various moments, platforms, and audiences [3].

1.2.3. Personalized Generation

Personalized generation refers to the use of data-driven technology to create customized content tailored to users' characteristics and preferences [4]. By analyzing user behavior, interests, and emotional states, this technology dynamically adjusts and optimizes content to enhance relevance and effectiveness. In marketing, personalized generation enables companies to move beyond the "one size fits all" approach, providing each user with a unique and tailored experience. Its applications extend beyond content presentation to include the optimization of user engagement channels and timing. By personalizing content, companies can better align with user expectations, improve conversion rates and customer satisfaction, and ultimately enhance their brand competitiveness and market influence.

2. The Application Basis of Affective Computing

2.1. Emotional Data Collection and Analysis

The collection and analysis of emotional data represent the initial step in applying affective computing, with the core focus being the extraction of user emotional features from multi-source data. Data collection includes both behavioral and text data. Behavioral data encompasses user interactions such as browsing trajectories, advertisement clicks, and consumption decisions, including metrics like stay time, click frequency, and navigation paths. This type of data reflects users' implicit emotional responses to content. Text data, on the other hand, involves explicit expressions such as user comments, social interactions, and feedback messages [5]. Emotional keywords and semantic tendencies are analyzed using natural language processing technology (As shown in Table 1).

Table 1. Emotional data collection and analysis framework.

Dimensions	Core contents
Data type	1.Behavior data: browsing clicks, length of stay, etc. (implicit emotion) 2.Text data: comments, dynamic, etc. (explicit emotion)
Analysis method	1. Use the algorithm to assess the positive, negative, or intensity of emotion. 2. Combine data such as voice and expression to improve accuracy
Goal	Transform the emotional signal into structured data to prepare for subsequent modeling

In terms of analysis methods, machine learning algorithms and emotion dictionary models facilitate the quantification of emotional features. Classification algorithms, such as logistic regression and neural networks, are employed to determine the polarity of emotions, categorizing them as positive, negative, or neutral. Additionally, the intensity of emotional expression is calculated by integrating emotional intensity models, such as distinguishing between pleasure and ecstasy. Multi-modal data fusion technology combines non-textual data, including pronunciation, intonation, and facial expressions, to improve the accuracy of emotion recognition in real-world scenarios. The essence of this process lies in transforming users' fragmented emotional signals into structured data, which serves as a foundation for subsequent demand modeling.

2.2. User's Emotional Needs Model

The user's emotional demand model transforms the emotional characteristics of data into the core elements of marketing writing by constructing an emotional tagging and demand mapping mechanism [5]. The model construction is divided into two steps: the first involves the layered construction of emotional portraits. Based on the results of emotional analysis, users are categorized into different emotional types and levels of emotional sensitivity. For instance, users who purchase maternal and child products may be labeled as highly sensitive to safety requirements. Conversely, consumers who purchase technology products are often characterized as innovative and curious, forming a distinct emotional labeling system (As shown in Table 2).

Table 2. Construction of user's emotional needs model.

Model level	How to do	Examples
1. Layered portraits	Group users by sentiment type (e.g. security needs, curiosity) and sensitivity (high sensitivity/rationality)	The maternal and child products are labeled as 'safety oriented', and the tourism products are labeled as 'pleasure oriented'.

2. Demand mapping	Match different writing styles to different emotional users; For anxious users, emphasize "reliable" solutions. Tell humorous stories to pleasant users.	The copywriter first presents the anxiety scene, then introduces the product plan, and finally "regains control."
Value	No longer write a copywriting by feeling, use data to make the content fit the user's emotions	

Secondly, there is the mapping transformation between emotion and demand, which involves establishing association rules between emotional labels and writing elements. For example, in health product scenarios, anxious users are more common, and advertising copy needs to emphasize deterministic solutions and incorporate emotional keywords such as "peaceful" and "reliable." For pleasant users, such as customers purchasing fast-moving consumer goods, the focus shifts to scene narration, triggering emotional resonance through a relaxed and humorous tone [6]. In conclusion, the mapping mechanism overcomes the limitations of traditional marketing's experience-based empathy, transforming creative writing from subjective intuition to data-driven, precise matching, and ensuring that content tonality aligns with users' emotional needs.

2.3. The Impact of Technology on Marketing Writing

Affective computing fundamentally reconstructs the logical paradigm of marketing writing and promotes its transformation from experience-driven to data-driven. In the traditional approach, creative writing relies on the writer's subjective experience and industry practices, often resulting in content that is homogenized and making it difficult to accurately connect with the user's emotions [7]. After technical intervention, personalized content that meets users' emotional preferences can be dynamically generated in real time, based on emotional time. For example, based on the emotional tendency of users in browsing history, the narrative perspective of copywriting is automatically adjusted. The use of the first personal pronoun strengthens the sense of substitution, while the first personal pronoun also enhances professionalism. Optimizing the emotional impact of keywords, such as upgrading recommendations to strong recommendations, better aligns with users who have high emotional sensitivity (As shown in Table 3).

Table 3. Comparison of technology-driven marketing writing and innovation.

Impact	Previous issues	Improvement	Examples of optimization
Writing logic	Relying on experience; the content is similar; can't grasp the mood	Write according to the user's real-time emotional data: Change personal pronoun (me/him); Adjust keyword strength	The copy for skin care products shifted from emphasizing packaging to highlighting efficacy, resulting in a 30% increase in conversion rate.
Feedback and adjustment	After writing, the impact is not considered.	Real-time observation data (click rate / conversion rate), immediately change the strategy	The survey revealed that young people prefer question-based copywriting, such as 'Have you faced XX problems?',

			resulting in a 25% increase in interaction rates.
The final effect	Content has no appeal and effect	Content and marketing objectives linked to continuous optimization	

Technology is utilized to establish a closed-loop mechanism that enables real-time feedback and policy adjustments. By tracking users' emotional feedback on the content, such as interactive data and secondary communication rates, the system can optimize the writing strategy in real time. For instance, if a specific type of copywriting has a high click-through rate but a low conversion rate, it may indicate a disconnect between the emotional resonance and the product's selling points [7]. Technicians can adjust emotional trigger points and information transmission priorities accordingly. Dynamic optimization enables marketing writing to evolve from one-time creation to continuous, iterative communication. This approach significantly enhances the emotional engagement of content and improves marketing efficiency.

3. The Method of Generating Personalized Creative Writing

3.1. Emotion-Based Customer Segmentation

Emotion-based customer segmentation leverages emotional data features to achieve precise categorization through a multi-dimensional labeling system. This segmentation primarily considers emotional types and emotional sensitivity. Emotional types refer to the dominant emotional tendencies of users in specific scenarios, such as the anxiety experienced by users of health-related products or the pleasure derived by users of entertainment products [8]. Emotional sensitivity reflects the intensity of a user's response to emotional stimuli, which can be categorized as either high sensitivity or low sensitivity. Highly sensitive individuals are more easily influenced by emotional expressions, while those with low sensitivity tend to prioritize rational information (As shown in Figure 1).

Figure 1. Three layers of emotional creation engine schematic diagram.

During the segmentation process, the system dynamically updates user profiles using real-time emotional data [6]. For example, when browsing maternal and child products, e-commerce users may be categorized as having safety-oriented needs. Conversely, when exploring tourism products, they may be classified as seeking pleasure-oriented experiences. This dynamic labeling adapts to the context, overcoming the limitations of traditional segmentation methods. As a result, content generation can more accurately align with the emotional needs of users in specific scenarios, providing a targeted foundation for personalized writing.

3.2. The Technical Path of Content Generation

The technical path of content generation centers on affective computing, with text customization achieved through natural language generation (NLG) and an emotional logic framework. NLG technology automatically adjusts language style based on the user's emotional tags: for highly sensitive users, it generates copywriting rich in metaphors and scene descriptions, such as the warm expression of "always protecting the baby" for maternal and child products. For low-sensitive users, the focus shifts to data and functional expression; for instance, in the case of technological products, rational demonstrations are emphasized, with accuracy reaching 99%.

In terms of content structure, technicians design a narrative framework guided by an emotional curve. Initially, user attention is captured by identifying customer pain points. Trust is then built by presenting solutions. Finally, memory is reinforced through value sublimation. For example, health-related copywriting begins by vividly describing a scene of late-night anxiety to evoke empathy. It then introduces an analysis of the product's composition to establish professionalism and authority [9]. The emotional loop is closed by presenting a vision of regaining control, ensuring the content resonates with the user's emotions.

3.3. Cross-Channel Adaptation Strategy

The cross-channel adaptation strategy aims to dynamically adjust the form and intensity of emotional expression, taking into account differences in media attributes and user scenarios. Social media platforms prioritize interactivity and immediacy, so content should adopt colloquial expressions and incorporate strong emotional symbols. For example, in short video copy, certain words are used to create a sense of urgency, including "best seller" and "rush to snap up." Email marketing emphasizes professionalism and depth, adopting a structured narrative that explains product advantages point by point, matches user testimony, and conveys emotional value within a rational framework [10].

It is necessary to combine the product attributes with the emotional adaptability of the scenes. For the promotion of luxury goods, the website highlights the legacy of exceptional high-end quality and creates an immersive unpacking experience on Xiaohongshu. Fast-moving consumer goods emphasize the importance of cost performance on e-commerce details pages and evoke consumers' emotions through visually appealing graphics and text on social media, thereby triggering consumption. This adaptation mechanism ensures emotional expression across different channels retains brand tonality while addressing varying emotional expectations of users.

4. Effect Evaluation System of Creative Writing

4.1. Evaluation Dimension

The evaluation of creative writing effects is constructed from three dimensions: emotion, behavior, and cognition. The emotional dimension examines the connection between content and users, including the intensity of emotional arousal and emotional consistency. Emotional arousal is measured by the emotional polarity, such as the proportion of positive emotions, and intensity, such as the level of pleasure and shock experienced by users. Emotional consistency evaluates the alignment between the emotional tone of content delivery and users' expectations, such as whether the promotional materials for maternal and child products meet the needs of the target audience.

Behavioral evaluation is based on user interaction data, including click-through rates, forwarding rates, and conversion rates [7]. The click-through rate reflects the emotional appeal of the title and content, the forwarding rate indicates the emotional value of the content that motivates users to share socially, and the conversion rate directly measures the efficiency of transforming users' emotional resonance into consumption behavior. The cognitive dimension focuses on the effectiveness of brand information transmission, such as memorability, which is assessed through the retention rate of core selling points. It also includes the degree of acceptance, such as the acceptance of product value propositions, and quantifies the influence of content on cognition using user research or semantic analysis techniques (As shown in Figure 2).

Figure 2. Three-dimensional closed loop of creative writing effect evaluation.

4.2. Evaluation Methods

The evaluation method employs a combination of a multi-index comprehensive model and a dynamic tracking mechanism. The multi-index model integrates three-dimensional data by creating a weighted system comprising emotional indicators such as resonance, behavioral indicators like interaction rate, and cognitive indicators including memorability. Additionally, it is dynamically adjusted according to marketing objectives [11]. For instance, during the brand exposure stage, the emphasis is placed on emotion and cognition, whereas in the promotion and transformation stage, behavioral metrics are prioritized. To determine weight, a machine learning algorithm can be utilized to identify the index combination with the highest correlation to marketing objectives, based on historical data training.

The dynamic tracking mechanism employs a real-time data acquisition system to continuously monitor user feedback after the content is released. For example, if the click rate of a copy is high but the conversion rate is low, the system automatically retrieves sentiment analysis results [12]. If it is determined that the emotional resonance of the content focuses on non-core selling points, such as copywriting related to skin care products overemphasizing packaging design rather than efficacy, it is flagged as emotional dislocation. This provides direction for subsequent optimization. Real-time evaluation eliminates the delays associated with post-evaluation.

4.3. Closed Loop of Evaluation and Optimization

The closed loop of evaluation and optimization is an iterative mechanism for integrating feedback data into the content generation process. Firstly, the evaluation results are utilized to refine the affective computing model. For instance, if the evaluation indicates that a specific user group responds negatively to certain professional terms, the keyword library within the model is adjusted to reduce the frequency of such terms for that audience. Secondly, the closed-loop mechanism facilitates the dynamic iteration of writing strategies. For example, evaluations may reveal that younger audiences exhibit stronger emotional responses to interactive questions. Consequently, the system updates the copywriting template for this demographic, incorporating sentence patterns such as "Have you encountered any problems?" to enhance engagement.

In the closed-loop process, a three-layer feedback loop is essential, encompassing data, strategy, and content [13]. The data layer integrates evaluation indicators, the strategy layer interprets the emotional demand changes reflected in the data, and the content layer adjusts the generation logic accordingly. For example, evaluations may reveal that users of health products have shifted their emotional focus from security to independent health management. This insight prompts the strategy layer to redefine core keywords and guides the content layer to reconstruct the narrative framework, thereby forming a comprehensive closed loop from evaluation to optimization.

5. Challenges and Future Trends

5.1. Challenges

The application of affective computing in marketing creative writing faces multiple challenges. One significant issue is the boundary between data privacy and ethics. Emotional data collection involves sensitive information, such as user behavior trajectories and text feedback. Improper handling of this data may result in privacy breaches. For instance, analyzing emotional tendencies through users' social interactions can inadvertently infringe on the privacy of their psychological states. Furthermore, the use of technology-driven personalized generation raises concerns about potential emotional manipulation. Over-reliance on algorithms to align with users' emotional needs may lead to content designs that overly cater to emotional preferences, thereby diminishing users' capacity for independent judgment.

Another challenge is the risk of content homogenization due to technical limitations. Affective computing models rely on historical data for training, which can reinforce specific emotional expression styles, causing copywriting across different brands to exhibit similar tones and narrative structures. For example, advertising for maternal and child products often employs safe and warm expressions, leading to creative convergence. Additionally, the accuracy of cross-cultural emotion recognition remains inadequate. Cultural differences in emotional expression, such as the implicit emotions common in Eastern cultures versus the explicit expressions prevalent in Western cultures, pose significant challenges. Current technologies struggle to adapt to diverse contexts, which may result in emotional misjudgments.

5.2. Development Trends

Future development will emphasize the integration of technology, the enhancement of man-machine collaboration, and the promotion of ethical frameworks. Multi-modal emotion data fusion is critical, as combining multidimensional data such as text, voice, images, and physiological signals—including heart rate and facial micro-expressions—can significantly enhance the accuracy of emotion analysis. For example, by analyzing the visual elements of short video content and monitoring users' physiological responses while viewing, emotional resonance can be captured more effectively.

The man-machine collaborative creation model is expected to become mainstream. In this model, AI manages emotional data processing and basic text generation, while creative professionals focus on emotional strategy and narrative design. This division of labor balances the precision of machines with human creativity [12]. For instance, AI can generate multiple versions of copywriting based on user emotional tags, while copywriters refine elements such as metaphor, rhetoric, and emotional tone, ensuring both efficiency and creativity.

Intelligent evaluation systems will also advance to enable real-time prediction. Using reinforcement learning algorithms, these systems can simulate the emotional reactions of various user groups before content is released, predict interaction outcomes, and automatically adjust writing strategies. This shifts the focus from post-evaluation to pre-optimization. Additionally, cross-domain technology integration will play a pivotal role, particularly in creating immersive emotional interactions within metaverse environments [9]. Establishing a transparent and ethical framework for the use of emotional data through blockchain technology will also be essential to balance personalized user experiences with robust privacy protection.

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