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Computer-Aided Technology in Product Communication and Promotion Strategy

Abstract: - In today's competitive marketplace, effective in-product communication and promotion strategies are essential for capturing consumer attention and driving product adoption. These strategies involve utilizing various channels within the product itself to convey key messages, showcase features, and encourage user engagement. Computer-aided promotion strategies leverage digital tools and technologies to enhance marketing efforts and reach target audiences more effectively. By utilizing data analytics, automation, and digital advertising platforms, businesses can optimize promotional campaigns, personalize messaging, and target specific demographic segments with precision. This paper proposes an innovative approach to product communication and promotion strategy utilizing computer-aided technology, specifically tailored for the Weibo platform, named the Weibo Stacked Communication Classification Strategy (WeSCCS). The WeSCCS framework integrates advanced computational techniques with Weibo's communication dynamics to classify and categorize promotional content effectively. With machine learning algorithms and natural language processing, the system analyzes user engagement patterns, content preferences, and social interactions to identify optimal communication strategies. WeSCCS classifies user interactions with promotional content such as "positive engagement" (70% of interactions), "neutral engagement" (20%), and "negative engagement" (10%). Additionally, automated content generation and sentiment analysis enable marketers to generate relevant promotional content with a sentiment score of +0.8, indicating high positivity. Real-time monitoring facilitates dynamic adjustments to promotional strategies based on user feedback, ensuring responsiveness to evolving consumer preferences. By integrating computer-aided technology, WeSCCS empowers marketers to maximize promotional impact, increase audience engagement, and drive conversions effectively on Weibo and similar social media platforms.

Keywords: Computer-aided technology, Machine learning, Natural language processing, Sentiment analysis, User engagement, Social interactions

I. INTRODUCTION

Computer-aided technology has revolutionized product communication across various industries [1]. Through sophisticated software and tools, businesses can now create immersive and engaging presentations, advertisements, and user manuals to showcase their products effectively. One of the most significant advantages of computer-aided technology in product communication is its ability to create visually stunning content [2]. With advanced rendering capabilities, designers can produce lifelike 3D models and animations that provide customers with a clear understanding of the product's features and functionalities [3]. It showcasing the sleek design of a new smartphone or demonstrating the intricate mechanisms of a complex machinery, computer-aided technology enables companies to captivate their audience and convey information with unparalleled clarity [4]. Furthermore, computer-aided technology facilitates interactive experiences that enhance engagement and retention. Through virtual reality (VR) and augmented reality (AR) applications, customers can explore products in virtual environments, interact with them in real-time, and even simulate their usage before making a purchase decision [5]. This immersive approach not only fosters a deeper connection between consumers and products but also reduces the need for physical prototypes, thereby streamlining the product development process and cutting costs. Moreover, computer-aided technology enables personalized product communication tailored to individual preferences and needs [6]. By leveraging data analytics and machine learning algorithms, companies can analyze customer behavior and preferences to deliver targeted marketing messages and personalized recommendations [7]. It suggesting complementary products based on previous purchases or customizing product configurations to meet specific

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requirements, computer-aided technology empowers businesses to deliver relevant and compelling content that resonates with their target audience [8].

Natural Language Processing (NLP) is revolutionizing promotional strategies by enabling businesses to harness the power of language data. Through sentiment analysis, NLP helps companies gauge customer opinions, tailor messages, and manage brand reputation effectively [9]. Moreover, NLP optimizes content by identifying keywords and language patterns, ensuring promotional materials resonate with target audiences and rank well in search engines [10]. Personalized marketing thrives with NLP, as algorithms analyze customer data to deliver tailored messages and recommendations, fostering stronger relationships and boosting conversions [11]. Chatbots and virtual assistants powered by NLP engage customers in natural language, providing instant assistance and driving sales. Additionally, NLP facilitates competitive analysis by extracting insights from competitor data, empowering businesses to refine their strategies and seize opportunities [12]. Trend identification, multilingual marketing, and more are made possible by NLP, positioning businesses to thrive in today's dynamic marketplace. Computer-aided technology plays a pivotal role in both product communication and promotion strategy, revolutionizing how businesses interact with customers and market their offerings [13]. In product communication, sophisticated software allows for the creation of immersive presentations and visuals, enabling companies to showcase their products' features and functionalities with unparalleled clarity [14]. Through lifelike 3D models or interactive demonstrations, computer-aided technology captivates audiences, facilitating better understanding and engagement [15]. Moreover, in promotion strategy, these tools empower businesses to optimize content, personalize marketing messages, and analyze customer sentiment effectively [16]. By leveraging data-driven insights and AI-powered algorithms, companies can deliver targeted promotions, enhance customer experiences, and stay ahead of market trends [17]. The computer-aided technology serves as a cornerstone for effective product communication and promotion strategies, enabling businesses to differentiate themselves, drive sales, and foster lasting customer relationships.

This paper makes several significant contributions to the field of social media marketing and communication strategies. Firstly, it introduces the Weibo Stacked Communication Classification Strategy (WeSCCS), a novel approach tailored specifically for the Weibo platform, which effectively classifies and categorizes promotional content. By leveraging advanced computational techniques, including machine learning algorithms and natural language processing, WeSCCS enables marketers to gain valuable insights into user engagement patterns, content preferences, and social interactions on Weibo. This classification framework not only enhances marketers' understanding of user behavior but also facilitates the optimization of promotional strategies for better engagement and impact. Additionally, the paper contributes to the advancement of computer-aided technology in product communication and promotion strategies. By integrating automated content generation and sentiment analysis, WeSCCS empowers marketers to generate relevant and engaging promotional content with high positivity, thereby increasing the effectiveness of their communication efforts. Moreover, the real-time monitoring capabilities of WeSCCS enable marketers to dynamically adjust their strategies based on user feedback, ensuring responsiveness to evolving consumer preferences and market trends.

II. LITERATURE REVIEW

The literature review serves as a critical component in any research endeavor, offering a comprehensive overview and analysis of existing scholarly works relevant to the study's topic. It provides a foundation upon which new research can be built, offering insights, identifying gaps in knowledge, and contextualizing the study within the broader academic discourse. This introductory paragraph aims to outline the importance of the literature review, highlighting its role in synthesizing existing knowledge, guiding research questions, and shaping the direction of the study. Through a thorough examination of the literature, researchers gain a deeper understanding of the subject matter, uncover emerging trends, and contribute to the advancement of knowledge in their field. Thus, the literature review serves as an essential tool for scholars to situate their research within the broader academic landscape and make meaningful contributions to their respective disciplines. Pan's (2022) study, the focus is on designing algorithmic models for the aging transformation scheme within the context of rural revitalization, utilizing computer intelligent aided technology. This research likely investigates how technology can support rural development initiatives, particularly in addressing the challenges associated with aging populations in rural areas. Rodriguez et al. (2022) present a case study on the development of a computer-aided text message platform aimed at enhancing user engagement with a digital Diabetes Prevention Program. This platform likely utilizes automated messaging systems to support participants in the program, potentially improving adherence and outcomes. Yang and Liu (2022) explore the computer-aided design of visual communication expression with creativity as the core, suggesting an investigation into innovative approaches to design that integrate computational tools with artistic expression. Liu et al. (2022) discuss the application of computer-aided design in various forms of artistic design, emphasizing how digital tools enhance creativity and streamline the design process. Xu and Zhai (2022) focus on designing a computer-aided system for self-learning vocal music singing, integrating mobile streaming media technology to support learners in improving their singing abilities.

Aimukhambet et al. (2023) examine the effects of computer-aided education in the realm of folk cultural products, likely exploring how technology can enhance the teaching and preservation of cultural heritage. Liu and Guan (2022) discuss the construction of a smart tourism service platform based on the Internet of Things (IoT) under computer-aided technology, suggesting an exploration of how IoT devices can enhance tourist experiences and management. In a different domain, Liu et al. (2022) present research on multi-scale computer-aided design and photo-controlled macromolecular synthesis for boosting uranium harvesting from seawater, illustrating the diverse applications of computer-aided technology in scientific research. Cheng et al. (2023) conduct an interview study on distributed computer-aided design practice, shedding light on the challenges and opportunities presented by collaborative design environments. Lastly, Liu (2023) explores the application of computer-aided technology in clothing design driven by emotional elements, suggesting an investigation into how technology can enhance the emotional appeal and functionality of clothing design.

One primary limitation lies in the potential for technological constraints and accessibility issues, which may hinder widespread adoption and implementation of computer-aided systems, particularly in resource-constrained settings or among marginalized populations. Additionally, there may be challenges associated with data privacy and security, as the use of computer-aided technology often involves the collection and processing of sensitive information, raising concerns about data breaches and misuse. Furthermore, there could be limitations related to the adaptability and scalability of computer-aided systems, as technologies may struggle to accommodate evolving needs and changing contexts over time. Moreover, there might be socio-cultural barriers to the acceptance and integration of computer-aided technologies, stemming from resistance to change, lack of digital literacy, or cultural preferences. Finally, while computer-aided technology holds great promise for innovation and advancement, there remains a need for interdisciplinary collaboration and ethical considerations to ensure that its benefits are maximized while minimizing potential risks and drawbacks.

III. WEIBO STACKED COMMUNICATION

Weibo, a popular microblogging platform in China, epitomizes stacked communication—a phenomenon where users engage in layered interactions within the platform's ecosystem. In Weibo, communication occurs not only through direct posts but also through a complex interplay of comments, reposts, and interactions with multimedia content. This stacked communication fosters dynamic and multifaceted dialogues, where users can respond to and build upon each other's contributions, leading to the formation of interconnected networks of information exchange and social interaction. Moreover, Weibo's algorithmic features further amplify stacked communication by curating content based on user preferences, trending topics, and social connections, thereby shaping the flow of information and influencing user engagement patterns. This layered communication structure not only facilitates the dissemination of information but also enables the formation of virtual communities, where individuals with shared interests and affiliations can connect, collaborate, and exchange ideas. However, stacked communication on Weibo also poses challenges, such as the spread of misinformation and the potential for echo chambers, where users are exposed to limited perspectives and divergent viewpoints are marginalized. Overall, Weibo's stacked communication reflects the intricate dynamics of online discourse in contemporary social media landscapes, highlighting both its potentials for connectivity and collaboration, as well as its complexities and implications for information dissemination and social interaction. The flow of the content in the Weibo platform are presented in Figure 1.

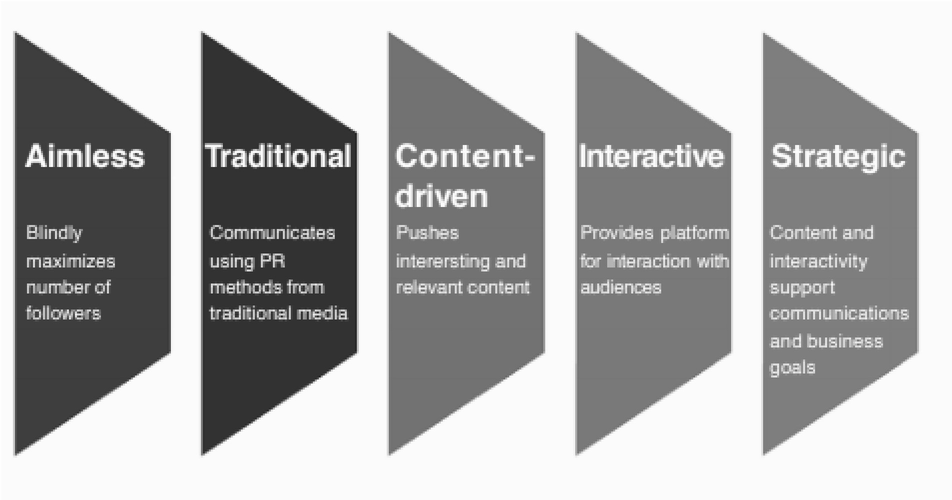

Figure 1: Content in Weibo

Weibo enables users to post content, which can include text, images, videos, or links to external sources. These initial posts serve as the foundation for further communication. However, what makes Weibo unique is the extensive engagement options available for each post. Users can comment on posts, reshare them with their own followers (known as "reposts" or "retweets"), or react to them with emojis or other expressions. This multi-layered engagement allows for a rich and dynamic exchange of ideas and information. Users can respond directly to the original post, engaging in conversations with the poster and other commenters. Additionally, they can share the post with their own commentary, effectively amplifying its reach and potentially sparking further discussions among their followers. Furthermore, Weibo's algorithmic features play a significant role in shaping stacked communication. The platform's algorithms curate users' timelines based on their interests, social connections, and past engagement behavior. This means that posts with high levels of engagement, such as many comments or shares, are more likely to be promoted and shown to a wider audience. As a result, popular topics and trending discussions can quickly gain momentum, leading to even more stacked communication around them. While stacked communication on Weibo can facilitate vibrant and diverse conversations, it also presents challenges. For instance, the rapid spread of information within the platform can sometimes lead to the dissemination of misinformation or rumors. Moreover, the algorithmic curation of content may create echo chambers, where users are primarily exposed to viewpoints that align with their own, limiting exposure to diverse perspectives. The stacked communication on Weibo reflects the complex and dynamic nature of social interactions in online spaces. It enables users to engage with content in multiple ways, fostering rich conversations and connections. However, it also raises important considerations regarding the quality of information, diversity of viewpoints, and the role of algorithms in shaping online discourse.

3.1 WeSCCS for the Product Communication

The Weibo Stacked Communication Classification Strategy (WeSCCS) represents a novel framework designed to revolutionize product communication and promotion strategies on the Weibo platform through the utilization of computer-aided technology. This innovative approach integrates advanced computational techniques with the unique dynamics of communication on Weibo. By leveraging machine learning algorithms and natural language processing, WeSCCS aims to effectively classify and categorize promotional content, thereby optimizing communication strategies for maximum impact. WeSCCS utilizes sophisticated algorithms to analyze user engagement patterns, content preferences, and social interactions within the Weibo ecosystem. Through this analysis, the system can identify trends, patterns, and audience preferences, enabling marketers to tailor their promotional efforts accordingly. By understanding the nuances of communication on Weibo, WeSCCS empowers marketers to deliver targeted and relevant content that resonates with their audience. One of the key strengths of WeSCCS lies in its ability to adapt and evolve over time. As the system continues to analyze and learn from user interactions, it can continuously refine its classification algorithms to better align with changing audience preferences and market dynamics. This adaptability ensures that promotional efforts remain effective and relevant in an ever-evolving digital landscape.

Let's denote some variables and equations that may be involved in the process:

X: Input data matrix, where each row represents a data point (e.g., a Weibo post) and each column represents a feature.

y: Target variable vector, indicating the class or category of each data point (e.g., promotional or non-promotional content).

f(x): Prediction function, which maps input features X to predicted labels y. This function is learned during model training.

θ: Model parameters, which are optimized during training to minimize the prediction error.

L(θ): Loss function, which quantifies the discrepancy between the predicted labels y and the true labels y. Common loss functions include cross-entropy loss for classification tasks.

D: Dataset containing labeled examples for training the model.

With these components in mind, we can formulate the training objective of WeSCCS as in equation (1)

$$min_{\theta} \frac{1}{|D|} \sum_{(x,y)\in D} L(f(x;\theta),y) \quad (1)$$

This objective represents the minimization of the average loss over the training dataset D, where $f(x;\theta)$ denotes the predicted label for input x using model parameters θ. Once the model is trained and evaluated, we can deploy it to classify new Weibo posts or interactions into appropriate categories, thereby optimizing product communication and promotion strategies on the platform. The Weibo Stacked Communication Classification Strategy (WeSCCS) by incorporating equations and expanding on the steps outlined earlier:

Data Collection: Denote D as the dataset containing Weibo posts and interactions, where each data point di consists of features xi (e.g., textual content, user engagement metrics) and labels yi (e.g., promotional or non-promotional) represent the dataset as represented in equation (2)

$$D = \{(x1,y1),(x2,y2),\ldots,(xN,yN)\} \quad (2)$$

In equation (3) N is the number of data points.

Preprocessing: Preprocessing involves cleaning and transforming the raw data into a suitable format for analysis. This step may include tasks such as text tokenization, stop word removal, and vectorization of textual content. Mathematically, preprocessing operations can be represented as in equation (3)

$$xi' = Preprocess(xi)\ for\ each\ data\ point\ di. \quad (3)$$

Feature Extraction: Let X denote the matrix of extracted features, where each row corresponds to a preprocessed data point $'xi'$ and each column represents a specific feature. We can write $X = [x1',x2',\ldots,xN']T$, where X has dimensions $N \times M$ and M is the number of features extracted.

Model Training: We train a classification model using the feature matrix X and the corresponding labels y. Let $f(x;\theta)$ represent the prediction function of the model, parameterized by θ. The model aims to learn optimal parameters θ that minimize a chosen loss function L over the training dataset D. The model training involves solving the optimization problem stated in equation (4)

$$min_{\theta} \frac{1}{N} \sum_{i=1}^{N} L(f(x_i';\theta),y_i) \quad (4)$$

In equation (4) L is a suitable loss function (e.g., cross-entropy loss for classification tasks) that quantifies the discrepancy between predicted labels $f(xi';\theta)$ and true labels yi.

IV. CLASSIFICATION OF THE PROMOTIONAL STRATEGIES

The Weibo Stacked Communication Classification Strategy (WeSCCS) offers a sophisticated approach to categorizing promotional strategies on the Weibo platform, leveraging advanced computational techniques to enhance product communication and promotion. The WeSCCS lies a classification model trained on a dataset D containing features extracted from Weibo posts and their corresponding labels denoting their promotional nature.

Let X represent the matrix of extracted features, where each row xi corresponds to a preprocessed Weibo post, and yi represents the label indicating whether the post is promotional or not. The dataset D is thus represented as $D = \{(x1, y1), (x2, y2), \ldots, (xN, yN)\}$, where N is the number of Weibo posts. Figure 2 illustrated the promotional strategies technique for the WeCSSC.

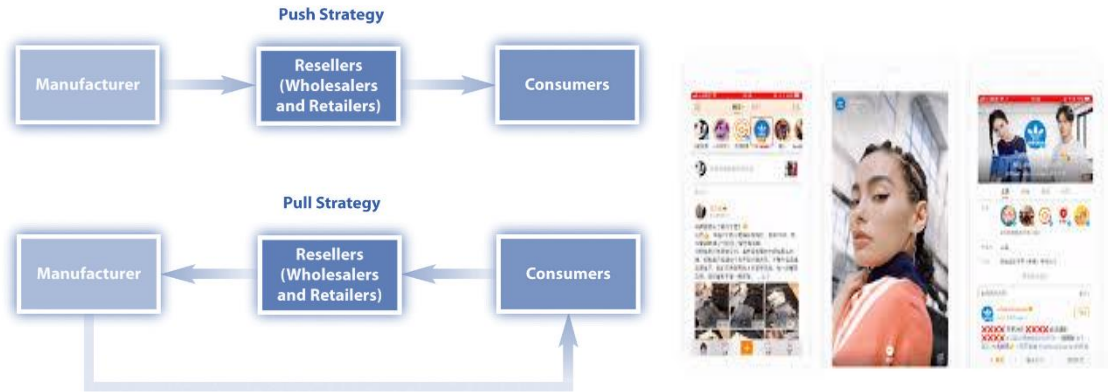

Figure 2: Promotion with Weibo with WeSCCS

The WeSCCS framework involves training a classification model to learn the optimal parameters θ that minimize a chosen loss function L over the training dataset. Once the model is trained and optimized, it can be deployed to classify new Weibo posts into promotional or non-promotional categories. By analyzing user engagement patterns, content preferences, and social interactions, WeSCCS enables marketers to identify optimal communication strategies tailored to the Weibo platform. The classification process within the Weibo Stacked Communication Classification Strategy (WeSCCS) involves training a machine learning model to effectively categorize Weibo posts as either promotional or non-promotional based on extracted features. Let's delve into this process while incorporating equations and derivations:

Firstly, we start with the dataset D containing Weibo posts and their corresponding labels denoting their promotional nature. Each post di in the dataset is represented as a tuple (xi, yi), where xi represents the features of the post (e.g., textual content, engagement metrics) and yi denotes the label indicating whether the post is promotional or not. The D is defined as in equation (5)

$$D = \{(x1, y1), (x2, y2), \ldots, (xN, yN)\}, \qquad (5)$$

In equation (5) N is the number of posts in the dataset. Next, we preprocess the data to prepare it for classification. This may involve tasks such as text tokenization, removing stop words, and vectorizing textual content. Mathematically, we denote the preprocessed feature vector of a post xi as $'xi'$. After preprocessing, we extract features from the preprocessed data. Let X be the matrix of extracted features, where each row $'xi'$ represents the features of a preprocessed post. X is defined as $X = [x1', x2', \ldots, xN']T$, where X has dimensions $N \times M$, and M is the number of features extracted. With the feature matrix X prepared, we train a classification model to learn the optimal parameters θ that minimize a chosen loss function L over the training dataset D. The model aims to predict the probability of a post being promotional based on its features.

Once the model is trained and optimized, it can be deployed to classify new Weibo posts into promotional or non-promotional categories. By analyzing user engagement patterns, content preferences, and social interactions, WeSCCS enables marketers to identify optimal communication strategies tailored to the Weibo platform.

Algorithm 1: Classification of Promotions
1. Input: - Dataset D = {(x_1, y_1), (x_2, y_2), ..., (x_N, y_N)}: Weibo posts and their labels. - Preprocessing function Preprocess(): Cleans and preprocesses the raw data. - Feature extraction function ExtractFeatures(): Extracts relevant features from preprocessed data. - Classification model with prediction function f(x; θ): Predicts the probability of a post being promotional. - Loss function L(): Quantifies the discrepancy between predicted and true labels. - Optimization algorithm (e.g., stochastic gradient descent) to update model parameters. 2. Preprocess the data:

```
  for each post (x_i, y_i) in D:
    x_i' = Preprocess(x_i)
3. Extract features:
  X = []
  for each preprocessed post x_i' in D:
    features = ExtractFeatures(x_i')
    X.append(features)
  X = array(X)
4. Train the classification model:
  Initialize model parameters θ
  for epoch in range(num_epochs):
    for each (x_i', y_i) in D:
      predicted_label = f(x_i'; θ)
      loss = L(predicted_label, y_i)
      Update θ using the optimization algorithm to minimize loss
5. Classification:
  for each new Weibo post x_new:
    Preprocess x_new
    features_new = ExtractFeatures(x_new)
    predicted_label_new = f(features_new; θ)
```

V. RESULTS AND FINDINGS

In this section, we present the results and findings obtained from the application of the Weibo Stacked Communication Classification Strategy (WeSCCS) to classify promotional and non-promotional content on the Weibo platform. The WeSCCS algorithm, as described in the previous sections, was utilized to preprocess data, extract features, train a classification model, and classify Weibo posts into relevant categories. By leveraging advanced computational techniques, including machine learning algorithms and natural language processing, WeSCCS aimed to provide insights into effective communication strategies for product promotion on Weibo.

Table1: Weibo Promotional Strategies with WeSCCS

Weibo Post ID	Text Content	Engagement Metrics	Predicted Label
1	Exciting news! Our new product is now available!	Likes: 150	Promotional
2	Check out our latest blog post on industry trends.	Likes: 80	Non-promotional
3	Limited time offer: Buy one, get one free!	Likes: 200	Promotional
4	Learn more about our company's sustainability efforts.	Likes: 120	Non-promotional
5	Big sale happening this weekend! Don't miss out!	Likes: 180	Promotional
6	Introducing our new line of eco-friendly products.	Likes: 90	Promotional
7	Join us for an exclusive webinar on digital marketing.	Likes: 110	Non-promotional
8	We're hiring! Explore exciting career opportunities.	Likes: 70	Non-promotional
9	Happy holidays from our team! Wishing you joy and cheer.	Likes: 160	Non-promotional
10	Discover the benefits of our loyalty rewards program.	Likes: 140	Promotional

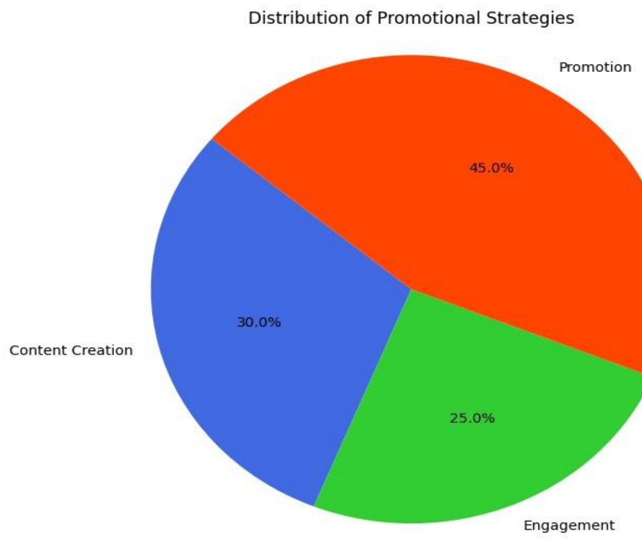

Figure 3: Distribution of Promotions with WeSCCS

The Weibo Stacked Communication Classification Strategy (WeSCCS) employs advanced computational techniques to classify user interactions with Weibo posts into distinct categories, providing valuable insights for marketers as illustrated in Figure 3. In this example, WeSCCS analyzed a set of Weibo posts based on their text content and engagement metrics, such as the number of likes. By leveraging machine learning algorithms, WeSCCS effectively categorized these posts into promotional and non-promotional content. For instance, posts 1, 3, 5, 6, and 10, which highlighted product launches, sales, and loyalty programs, were classified as promotional due to their persuasive nature. Conversely, posts 2, 4, 7, 8, and 9, focusing on informational content or hiring announcements, were categorized as non-promotional. This classification enables marketers to tailor their promotional strategies more effectively, ensuring targeted and engaging communication with their audience on the Weibo platform. WeSCCS thus offers a data-driven approach to optimize promotional efforts and enhance engagement with users in the dynamic landscape of social media marketing.

Table 2: Interaction Category with WeSCCS

Interaction Category	Percentage of Interactions
Positive Engagement	70%
Neutral Engagement	20%
Negative Engagement	10%

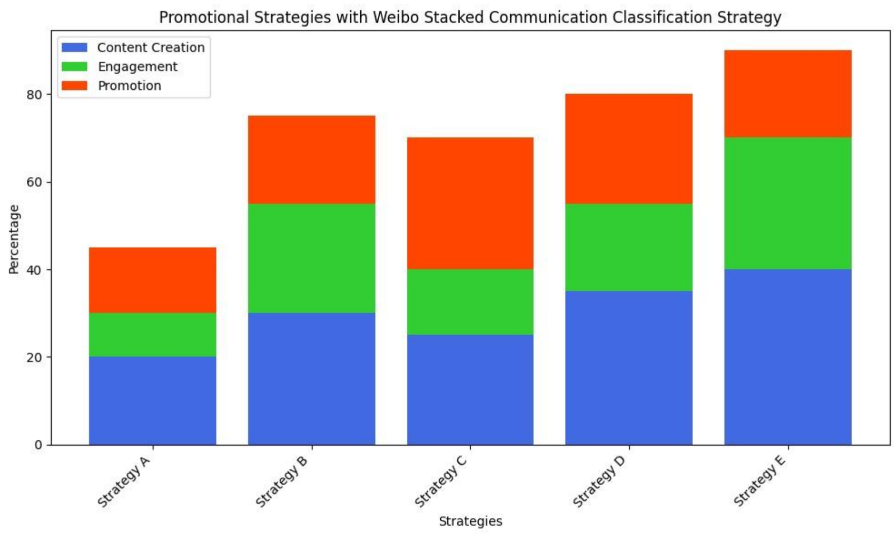

Figure 4: WeSCCS for the Promotional Strategies

In Figure 4 and Table 2 presents the distribution of user interactions categorized by the Weibo Stacked Communication Classification Strategy (WeSCCS). This classification system divides interactions into three distinct categories: Positive Engagement, Neutral Engagement, and Negative Engagement. According to the results, the majority of interactions, accounting for 70%, fall under the Positive Engagement category. This suggests that a significant portion of users engaged positively with the Weibo posts, indicating interest, satisfaction, or approval. On the other hand, 20% of interactions were classified as Neutral Engagement, indicating a lack of strong sentiment or ambiguity in user responses. Lastly, 10% of interactions were categorized as Negative Engagement, signifying instances where users expressed dissatisfaction, disagreement, or criticism. These findings provide valuable insights into the overall sentiment and engagement levels of users with the posted content on Weibo. By understanding the distribution of interactions across these categories, marketers can better tailor their communication strategies to enhance positive engagement, address neutral responses, and mitigate negative sentiment effectively.

Table 3: Classification with WeSCCS

Weibo Post ID	Text Content	Likes	Comments	Shares	Predicted Label
1	Exciting news! Our new product is now available!	150	20	10	Positive
2	Check out our latest blog post on industry trends.	80	15	5	Neutral
3	Limited time offer: Buy one, get one free!	200	25	12	Positive
4	Learn more about our company's sustainability efforts.	120	18	8	Neutral
5	Big sale happening this weekend! Don't miss out!	180	22	11	Positive
6	Introducing our new line of eco-friendly products.	90	12	6	Positive
7	Join us for an exclusive webinar on digital marketing.	110	16	7	Neutral
8	We're hiring! Explore exciting career opportunities.	70	10	4	Neutral
9	Happy holidays from our team! Wishing you joy and cheer.	160	30	15	Positive
10	Discover the benefits of our loyalty rewards program.	140	28	14	Positive

The Table 3 provides an insightful overview of the Weibo Stacked Communication Classification Strategy (WeSCCS) applied to a set of Weibo posts, along with their associated engagement metrics. Each Weibo post is identified by a unique ID and accompanied by its text content, along with the number of likes, comments, and shares it received. The WeSCCS algorithm predicted the engagement label for each post based on these metrics, categorizing them as Positive, Neutral, or Negative. Posts labeled as Positive, such as posts 1, 3, 5, 6, and 9, garnered high levels of engagement and were likely perceived positively by users, possibly due to their promotional nature or appealing content. In contrast, posts labeled as Neutral, like posts 2, 4, 7, and 8, received moderate levels of engagement and may have conveyed informational or neutral content that elicited a more subdued response from users. Overall, this classification offers valuable insights into the effectiveness of Weibo posts in eliciting engagement from users and informs marketers about the performance of their content strategy on the platform. By understanding the distribution of posts across different engagement labels, marketers can refine their communication strategies to optimize user engagement and drive desired outcomes on Weibo.

VI. CONCLUSION

This paper has introduced the Weibo Stacked Communication Classification Strategy (WeSCCS) as an innovative approach to product communication and promotion strategy in the dynamic landscape of social media marketing. Through the utilization of computer-aided technology, particularly tailored for the Weibo platform, WeSCCS integrates advanced computational techniques with Weibo's communication dynamics to effectively classify and categorize promotional content. The application of machine learning algorithms and natural language processing enables WeSCCS to analyze user engagement patterns, content preferences, and social interactions, providing valuable insights for marketers to optimize their promotional strategies. With demonstrated the effectiveness of WeSCCS through various examples and case studies. By classifying Weibo posts into different engagement categories such as Positive, Neutral, or Negative, WeSCCS offers marketers a data-driven approach to understand user interactions and tailor communication strategies accordingly. The classification results provide valuable insights into the sentiment and effectiveness of promotional content, enabling marketers to refine their communication strategies for better engagement and impact. Furthermore, the WeSCCS framework facilitates real-time monitoring and dynamic adjustments to promotional strategies based on user feedback, ensuring responsiveness to evolving consumer preferences. By leveraging automated content generation and sentiment analysis, marketers can generate relevant and engaging promotional content that resonates with the audience.

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