

The Role of Message Strategy Combinations, Perceived Risk, and Personalization in Chinese Cosmetic Short-Video Advertising: Insights from Taylor's Six-Segment Message Strategy Wheel

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Abstract — Given the rapid growth of the Chinese cosmetic short-video market, it is crucial for marketers to design tailored marketing content that aligns with the sales environment, which enables better adaptation to platform personalization algorithms and enhances profitability. Using Taylor's six-segment message strategy wheel as a classification framework, this study examines the impact of various message strategies and their combinations on consumer purchasing intention, within the scope of Chinese short-video advertisements. It also explores the certain strategy combinations influencing consumers' perceived risk and the moderating role of perceived risk in the relationship between message strategies, personalization, and purchasing intention. The findings indicate that individual message strategies do not significantly affect purchase intention; however, certain combinations do — "Sensory + Ration" enhances consumer interest, while "Routine + Ration" diminishes it. Moreover, the "Ego + Routine" combination can significantly increase consumer perceived risk, thus indirectly influence their purchasing intention. Notably, perceived risk does not significantly moderate the relationship between any message strategy (or combination) and consumer purchasing intention, but it does significantly moderate the relationship between personalization and consumer purchasing intention. While this study contributes to the understanding of message strategies, perceived risk, and personalization, it also acknowledges limitations related to evolving market dynamics and recommends future research to refine message typologies and moderation analyses through systematic testing.

Keywords — *Short Video, Advertising, Message Strategies, Consumer Purchasing intention, Personalization, Perceived Risk*

I. INTRODUCTION

With the increasing awareness of personal appearance and well-being, the global cosmetic market has experienced continuous growth, reaching a market value of \$299.77 billion in 2022 (Fortune Business Insights, 2023). By early 2021, China had already become the second-largest consumer market for cosmetic products worldwide (Xinhua News Agency, 2021), establishing itself as an indispensable part of the global cosmetic landscape. Simultaneously, the rapid development of Chinese short video platforms such as TikTok, Kuaishou, and Xiaohongshu cannot be overlooked. By 2023, the market value of these platforms expanded to 49.59 billion dollars, reflecting a 22.94% increase compared to 2022 (L. L. Thomala, 2024). The immense profitability of short video market has made short video advertising a powerful tool for sales promotion across various industries, including cosmetics.

The key reason behind this success lies in marketers' deep understanding of the factors stimulating consumers purchasing intentions on short video platforms. For example, recognizing the importance of targeting consumer needs, these platforms have developed highly sophisticated personalized promotion algorithms. Additionally, with the growing prevalence of in-app purchases (Ceci, 2025; TikTok, 2024), standardized consumer rights protection systems have been implemented to reduce their perceived purchase risks. Another critical factor they aim to tackle is the promotional content itself. Attitudes of influencers, or online bloggers with a substantial number of followers, play a pivotal role in shaping consumer opinions within the digital network (F. F. Leung et al., 2022). Collaborations between influencers and companies or independent marketers are now common, with influencers promoting specific products to targeted audiences. Therefore, it is essential for both influencers and sales professionals to design compelling promotional content that effectively highlights product benefits and makes consumers believe that the product is worth purchasing.

Nevertheless, promotional content is not a factor that platforms can directly standardize or control. Nearly all videos on short video platforms, including promotional advertisements, are essentially published by users themselves instead of cosmetic companies, making the development of a standardized approach to effective promotion particularly challenging and demanding. A growing body of literature has addressed this issue, seeking to identify specific features of short video content that can effectively stimulate consumers' purchasing intentions (Gong et al., 2021; Xiao et al., 2023; Pei, 2023). However, this results in diverse and fragmented analytical approaches, as they tend to focus on isolated aspects of video content, rather than employing a comprehensive framework to systematically categorize and examine advertisement elements. In spite of this gap in short video marketing, there are sophisticated and well-established classification methods of promotional content analysis in traditional marketing research, often referred to as "message strategies", which are comprehensive enough to provide a structured way of decoding and categorizing various ad content elements. Prior research has well-explored various facets of message strategies, such as typologies (Laskey et al., 1989, 1995; Taylor, 1999), effectiveness (Ahmed et al., 2024; White & Radic, 2014; Xiang et al., 2019), and the applicable conditions (Ahn et al., 2013a; Kalbani et al., 2022). What's more, since the promotional content in traditional commercials largely overlaps with that of short video ads, existing analytical frameworks can feasibly be applied to

dissect short video advertisements. However, again, these studies rarely address the mutual effects of message strategies, which is another noticeable gap, given that a single video advertisement often incorporates multiple strategies in reality.

To bridge these research gaps, this study adopts a reliable, generalizable, and consistent message strategy model to analyze short video ad content. By standardizing the promotional features in these videos, we aim to identify effective strategies or strategy combinations applicable to real-world cosmetic marketing. The selected model is Taylor (1999)'s six-segment message strategy wheel, a well-established traditional promotion framework still being widely used in contemporary advertising research (Ahn et al., 2013). This model categorizes message strategies into two contrasting approaches, each containing three distinct strategy types. After decoding the ad content, we then assess the effectiveness of these strategies. Beyond examining the impact of 6 individual strategies on consumer purchasing intention, we further investigate their interactions by analyzing all 15 possible pairwise combinations. This process offers deeper insights into how these strategies collectively shape consumer behavior.

What's more, to adopt a more nuanced approach to how different message strategies (or their combinations) work with other factors within real-world short video platforms, this study correlates them with personalization and perceived risk – two key concerns of cosmetic marketers that have long been demonstrated as having positive & negative influence on consumer purchasing intention, respectively (Almousa, 2011; Ariff et al., 2014; Elliot & Fowell, 2000; Gong et al., 2021; Graffagnino, 2024; Munikrishnan et al., 2023; Park et al., 2012; Tho et al., 2017; Zhang et al., 2012). Given that perceived risk tends to negatively impact consumer purchasing intention by introducing uncertainty in the overall online shopping environment (Forsythe & Shi, 2003; Qalati et al., 2021; Tho et al., 2017; Tsiakis, 2012), we hypothesize that perceived risk acts as a moderator between consumer purchasing intention and its other contributing factors. Prior research suggests that perceived risk significantly moderates relationships involving emotion-driven, non-cognitive factors (Jangir et al., 2022; Lavuri et al., 2022; Ozyer et al., 2014; Wangenheim & Bayón, 2004). Thus, this study retests these findings in the context of Chinese cosmetic marketing, specifically examining perceived risk's moderating role in: (1) The relationship between discretion-excluded personalization and consumer purchasing intention; (2) The relationship between discretion-included effective message strategies (or combinations) and consumer purchasing intention.

The videos extracted for this study are all from three of the most representative Chinese short video platforms — TikTok, WeChat Channels, and Rednote. Respondents were recruited from two different research platforms and were selected to approximate the profile of typical cosmetic product purchasers. Through a series of separate regression analyses, the findings reveal several key insights into the effectiveness of different message strategy combinations: The “sensory + rational” combination were found to have a positive and direct effect on consumer purchasing intention, while the “routine + rational” combination indicated a negative and direct influence. Moreover, although the “ego + routine” combination did not show a direct impact on purchasing intention, it indirectly and negatively affected it by significantly increasing perceived risk. This study also

corroborates previous research by confirming that perceived risk positively moderates the relationship between personalization and consumer purchasing intention but has no moderating effect between effective message strategy combinations and purchasing intention. The positive impact of personalization and the negative influence of perceived risk on consumer purchasing intention also align with findings from earlier studies in the field of cosmetic marketing. By highlighting these results, this research provides marketers with more precise and practical guidance to optimize their video advertisements for both reach and effectiveness. Chinese sales professionals in the cosmetic industry can use these insights to design more engaging, reliable, and consumer-focused short videos, thereby improving their sales performance.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

A. *Personalized cosmetic products advertisements on short video platforms*

Cosmetic products are formulations designed to enhance, alter, or maintain human appearances (Britannica, 2024). Recent studies indicate various factors influencing consumers' purchasing intention of cosmetic products, including brand loyalty (J. E. Lee et al., 2019), religious beliefs (Handriana et al., 2020), and cultural factors (Chen & Dermawan, 2020). Given the personal nature of these factors, creating individual customer profiles is essential for marketers to deliver promotions of targeted products to them. Coner (2003) described personalization as a method used by companies to match classified content with profiled users. This approach has been widely adopted in the short video industry, where content visibility is largely driven by platforms' embedded algorithms. This algorithm matches individual users with videos aligned with their preferences, which further manipulates their actual behaviors (Alvarado et al., 2020). TikTok, as one of the largest short video platforms both in China and worldwide, has effectively demonstrated the potential of combining short videos and personalized sales promotions together. In a survey conducted in 2021, 90% of respondents reported having seen promotional videos on TikTok, in which 41% of them had experienced purchasing the product advertised after watching those videos (Azpeitia, 2021). While continuing to build a solid user base, this e-commerce strategy of TikTok has constantly delivered satisfaction to its customers and boosted their loyalty to the brands (Ma & Yu, 2021). In alignment with previous literature describing the indispensable role that personalization played in boosting consumer purchasing intention, the following hypothesis is proposed:

H1. Personalization positively influences consumer purchasing intention.

In addition to personalization, which aligns individual customer needs with the functions of advertised products, the profitability of cosmetic video ads is largely shaped by their promotional content. On short video platforms, those contents are typically created by users themselves, which are flexible and do not often comply with rigid promotion guidelines. Users with a substantial follower base are regarded as influencers. They often maintain a symbiotic relationship with marketing firms, collaborating to promote designated products to a broader audience under their unique capabilities (Haenlein et al., 2020; F. F. Leung et al., 2022). As there is an increasing demand for influencers to create effective and

profitable short video ads themselves, substantial research attention has recently been paid to dissecting video ad promotional content and its influence on consumer purchasing decisions. For instance, Gong et al. (2021) focused on how the features of short video advertisements affect consumers' purchase behaviors. They found that three dimensions of published content features — received fitness, aesthetic quality, and content richness have a considerable impact on consumer purchasing intention. Xiao et al. (2023)'s study stated four key features of short video advertisements, including performance expectancy, entertainment, tie strength, and sales approach that strongly impact consumer engagement. Similarly, Pei (2023) identified key factors, including functional content, entertaining content, and socially interactive content in short video advertisements that positively influence consumer purchasing intention for cosmetic products. While most of those studies demonstrate a solid relationship between the promotional contents of short video ads and consumer purchasing intention, they focus on specific characteristics of the ads without offering a holistic view. Few of them decode the contents as a whole under a comprehensive model, limiting their ability to generalize “what to say” to effectively stimulate consumer purchasing intention. Without the use of consistent and rigorous models, those findings are often contentious or even contradictory (Tafesse & Wien, 2018). Therefore, this study seeks to address this gap by conceptualizing the entire ad content as “message strategies” and employing Taylor's six-segment message strategy wheel to decode, analyze, and categorize those strategies. This approach can provide more generalized and practical insights for real-world applications.

B. Message Strategies and Taylor's Six-Segment Message Strategy Wheel

Taylor (1999) described message strategies as the guiding principle for determining “what to say” in the planning process of advertising or marketing communications. He defined it as “a guiding approach to a company's or institution's promotional communication efforts for its products, services, or itself.” Rather than focusing solely on product attributes, message strategies emphasize more on how to effectively highlight and communicate the desirable features of a product. The effective use of message strategies can significantly and positively influence consumer behaviors and purchasing decisions (Al-Shammari et al., 2021; Tafesse & Wien, 2018). Therefore, to enhance marketing effectiveness, there is an ongoing need for both inclusive and specialized message strategy typologies that can help standardize and guide promotion practices.

In traditional market communication, a widely accepted way to categorize message strategies is the two-group message typology, which distinguishes message strategies by whether they are based on the informational approach or the emotional approach (Laskey et al., 1995). Informational message strategies target consumers' logical and reasonable cognitive responses, while emotional message strategies aim to evoke consumers' feelings and sensory reactions (C. Kim & Yang, 2017). This basic two-group message typology continues to be useful for classifying the contents of different social media postings today (Kusumasondjaja, 2018; Molina et al., 2020; Tafesse, 2020). Beyond the two-typology approach, other scholars have developed more complex, multi-group message typologies (X. Y. Leung et al., 2017), such as Kotler (1965)'s five different behavioral models, Simon (1971)'s ten category framework, Vaughn (1980)'s

FCB grid, and Taylor (1999)'s six-segment message strategy wheel, which offered more detailed guidelines for categorizing message strategies. Among these, Taylor's six-segment message strategy wheel stands out as a relatively comprehensive and reliable model built on the review, synthesis, and refinement of earlier works in this field (Kalbani et al., 2022).

Although Taylor's six-segment message strategy wheel classifies message strategies into multiple segments (categories), it fundamentally reflects the two-group message typology by dividing message strategies into ritual (emotional) and transmission (informational) views. Each view contains three distinct segments of message strategies. This treatment helps specify and quantify different types of message strategies while retaining the inclusiveness of the multi-group division method, which is critical for practical application. Specifically, the ritual view includes the ego, social, and sensory segments. The ego segment caters to consumers' emotional needs by helping them define and express their individual identities. The social segment emphasizes the social significance of products, enabling consumers to convey their identities within their related social groups. The sensory segment highlights the ability of products to provide consumers with pleasurable experiences, appealing to their five senses. Conversely, under the transmission view, the segments include routine, acute need, and ration. The routine segment motivates habitual purchasing behavior for products that consumers do not intend to spend large amounts of time gathering information. The acute need segment aims to build trust with consumers, persuading them to choose the product when time constraints limit their ability to gather information. The last segment, ration, addresses situations where consumers are realistic and actively seek information, focusing on rational decision-making processes.

Since its publication, Taylor's six-segment message strategy wheel has been long and widely adopted for classifying advertising message strategies. It is often used to analyze the circumstance of message strategy application within a specific product category, and within one, or over different timeframes. For instance, Golan & Zaidner (2008)'s study on online viral advertising used Taylor's framework to analyze 360 viral advertisements, revealing that ego-oriented appeals were the most frequently employed strategy by advertisers. Similarly, Lee et al. (2011) applied this model to examine how the U.S. financial service organizations' advertising strategies evolved from 2005 to 2009. They found out that ego and ration strategies became more prominent in financial service magazines after the 2008 economic crisis. Finneman et al. (2024) extended this approach by categorizing message strategies that appeared in 1934 newspaper advertisements, figuring out that essential and non-essential industries employed different message strategies. Furthermore, beyond simple categorization, some studies applying this model have also explored the impact of message strategies on audience engagement. C. Kim & Yang (2017)'s study analyzed the relationship between different message features and users' communication behaviors on Facebook, finding that “like” corresponded with sensory appeals, “comment” with ration appeals, and “share” with both sensory and ration appeals. A more recent study, R. Wang et al. (2023)'s study investigated consumer technology video ads, identifying that ego and sensory strategies could positively or negatively influence the number of video dislikes

correspondingly when combined with different target products.

Based on those previous studies, it is evident that Taylor's six-segment message strategy wheel can help advertisers distinguish between different message strategies (Ahn et al., 2013b) in various research approaches. However, none of the studies focusing on the six-segment message strategies' effect have explored any interaction between the six segments themselves. While many have noted the common use of multiple strategies within a single post, they tend to examine how the effect of one strategy differs from another, overlooking the potential joint effects of multiple strategies. In fact, different message strategies, when used together, are likely to have an additive effect on consumers' behavioral engagement (Tafesse & Wien, 2018). Organizing these strategies into a cohesive theme based on the target audience and media platform is crucial for achieving effective communication outcomes (Fajar, 2009; Ismunandar et al., 2023). Therefore, this study applies Taylor's model to categorize various message strategies and analyze their influences on consumers' purchase intention for cosmetic products, both individually and collectively. In the collective component of our analysis, we combine two of the six strategies to form 15 different "strategy groups," which are then treated as new independent variables. Given the complexity of interplay between message strategies and purchase intention, this study seeks to address the following exploratory hypotheses:

H2. Different message strategies and their combinations have varying effects on consumer purchasing intention.

H3. The combination of multiple message strategies yields stronger purchase intention compared to single strategies.

C. Consumer Perceived Risk and its Moderating Effect

To better leverage personalization algorithms and influencers' promotional capabilities, short video platforms often offer integrated e-commerce features, such as TikTok's and Rednote's "Shop" functions, and WeChat Channel's Mini Stores. Content creators can add purchase links under related short video advertisements, which take customers directly to the transaction page within the creator's virtual store. This setup provides customers with convenience and smooths the transition from match, promotion to sales revenue. The TikTok Shop serves as a representative case of the growing profitability associated with this model. In 2024, TikTok's global revenue from in-app purchases reached 3.7 billion, which is over 140 times higher than that in 2018 (Ceci, 2025).

Despite the huge commercial potential of short-video-based e-commerce, it faces certain challenges to be addressed. Online shopping is generally perceived as risky due to the inherent characteristics of its virtual environment (Almousa, 2011), since the online nature of these platforms prevents consumers from physically examining the products advertised (Foscht et al., 2013; Park et al., 2012). What's more, user-generated content on these platforms is freely accessible, which creates serious privacy concerns (Di Minin et al., 2021). Those risky attributes are quantified as perceived risk, which is defined as the uncertainty regarding potential negative outcomes when consumers make purchase decisions (S. M. Forsythe & Shi, 2003; Qalati et al., 2021; Tho et al., 2017; Tsiakis, 2012). Previous studies have identified various components of consumer perceived risk, including financial risk, performance risk, physical risk, time risk, and delivery

risk, among others (Ariffin et al., 2018; Jacoby & Kaplan, 1972; Masoud, 2013; Spence et al., 1970). Drawing on those literatures and considering the specific contexts of Chinese short video platforms, this study focuses on five components of consumer perceived risk: financial risk, product risk, time risk, social risk, and information security risk. These risks represent the types of concerns that Chinese consumers may experience after viewing the short video advertisements.

Numerous studies have demonstrated that perceived risk can negatively impact on consumer purchasing intention (Almousa, 2011; Ariff et al., 2014; Elliot & Fowell, 2000; Munikrishnan et al., 2023; Park et al., 2012; Tho et al., 2017; Zhang et al., 2012). Other studies have identified certain factors that contribute to perceived risk and its effect, such as online trust (Bauman & Bachmann, 2017; Qalati et al., 2021; P. C. S. Wu & Wang, 2011). Within this framework, contributors to perceived risk can indirectly affect consumers' purchasing intentions, making perceived risk a moderating variable. Consequently, understanding the factors that shape consumer perceived risk, as well as implementing policies and strategies to target these factors, are crucial for e-commerce operators to retain their customer base (Bauman & Bachmann, 2017; Tho et al., 2017). In this context, short-video content creators can potentially influence perceived risk through strategic messaging, as they can make certain desirable features of products, including those related to "safety" and quality assurance, become better promoted. By adopting or eliminating certain target message strategies, they can probably reduce consumers' perceived risk and, in turn, enhance their purchasing intention. Therefore, this study develops the following hypotheses:

H4. Perceived risk negatively influences consumer purchasing intention.

H5. Certain message strategies and combinations can directly influence perceived risk.

In addition to the mediating role of perceived risk, research has also investigated perceived risk's role as a moderator. Increased perceived risk can lead to higher overall levels of "problems" inside consumers' online purchasing environment, therefore impacting their satisfaction and acceptance of a product (Jangir et al., 2022; W. Wu et al., 2021). These moderating effects, which occur between consumer purchasing intention and its various contributing factors, can strengthen or weaken the relationship between them in high-risk situations. For example, v. Wangenheim & Bayón (2004) demonstrated that perceived communicator characteristics of word-of-mouth (WOM) strongly influence consumer decision-making. They also found that under high perceived risk — whether social/psychological or financial/functional — the dimensions of perceived risk positively moderate the impact of these perceived characteristics on decision-making. Similarly, Ozyer et al. (2014) observed that while consumers' utilitarian and hedonic motivation on search can both positively influence consumer purchasing intention, perceived risk can only act as a significant moderator on the hedonic side. Jangir et al. (2022) highlighted a significant moderating effect of perceived risk on the relationship between satisfaction and consumers' continued use of Fintech services, and noted that this effect becomes insignificant when perceived usefulness, rather than satisfaction, is the primary factor. These studies suggest that perceived risk commonly moderates the relationship between consumer purchasing intention and emotionally focused

factors that do not require consumers' deliberate trade-off processes. Given that certain messaging strategies align with consumers' ritual views (Taylor, 1999), and personalization can reduce the cognitive load of their purchasing decisions (Chandra et al., 2022), it is likely that perceived risk may also moderate the relationship between specific message strategies, or message strategy combinations, and consumer purchasing intention, as well as between personalization and consumer purchasing intention. Based on this inference, the study focuses on the following hypotheses:

H6. Perceived risk is more likely to positively moderate the effects of ritual message strategies (and their combinations) on consumer purchasing intention compared to transmission ones.

H7. Perceived risk positively moderates the effects of personalization on consumer purchasing intention.

D. Theoretical Framework Development

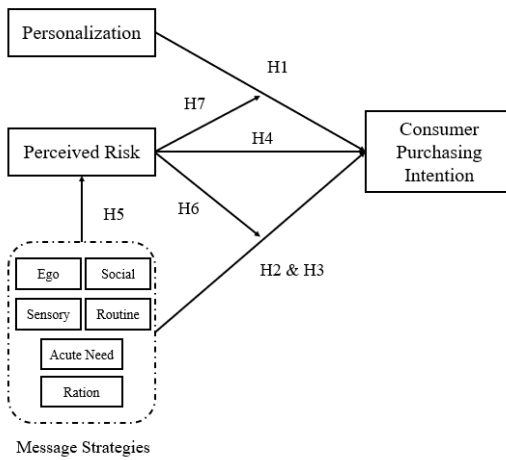


Fig. 1. Theoretical Framework

Fig.1 presents the research model developed from the previous literature review, simulating the real-world scenario of customers watching a cosmetic video advertisement. This model consists of four key components: personalization, perceived risk, message strategies, and consumer purchasing intention. Within the message strategies component, this study incorporates the six message segments inside Taylor's six-segment message strategy wheel, 15 possible combinations of these strategies, and the total number of strategies applied in a single ad. Hypotheses H1, H2, and H3 examine the primary factors influencing consumer purchasing intention, suggesting that marketers' use of message strategies, along with consumers' perceptions of personalization and perceived risk, may all contribute to consumers' purchasing decisions. H5 investigates how different aspects of message strategies influence consumers' perceived risk, while H6 and H7 explore the moderating effects of perceived risk in the relationships between the potentially effective message strategies, strategy combinations, personalization, and consumer purchasing intention. Although a comprehensive theoretical framework has been developed, this study addresses potential multicollinearity by analyzing the variables in separate regression models to enhance clarity and accuracy, especially in the message strategies segment.

III. RESEARCH METHODOLOGY

To ensure that the promotional videos collected as samples are comprehensive and representative, this study collects sample videos from three different Chinese short video platforms: TikTok, WeChat Channel, and Rednote. All three platforms have large user bases and hold leading positions in the Chinese short video market. TikTok and WeChat Channels ranked the top two in monthly usage (L. Y. Thomala, 2024). To better approximate the actual user composition of cosmetic products, we included Rednote in our sample selection, as it ranked fifth in overall popularity and has a predominant female user demographic (Yang, 2024). Sample videos are automatically and randomly generated by the platforms' own pushing mechanisms on the home page, and are gathered for future relevant content analysis. To minimize the impact of the platforms' built-in personalization algorithms, all sample videos are collected using newly created accounts, and no interacting behaviors (such as like, comment, and share) were performed during the video collection process.

Following the collection, a primary content analysis was conducted by a single coder, revealing that almost every cosmetic product recommendation video employed sensory strategies, probably due to the products' substantial decorative functions. Additionally, videos employing acute need or ration strategies constituted approximately 75% of the initial sample, while the videos employing ego, social, or routine messages accounted for only 40%, indicating a significant imbalance in message strategy usage distribution. To achieve a relatively balanced representation of message strategies, videos with acute need and ration strategies were randomly removed from the sample. However, due to practical challenges and limitations, the disparity between sensory strategies and the other five strategies was maintained after consideration. Furthermore, videos containing recommendations for multiple products were excluded from the sample, since the sequence in which products are introduced in advertisements could influence viewer engagement (Brunel & Nelson, 2003; Terry, 2005). After these adjustments, a final sample of 45 videos was established, with 15 videos sourced from each platform and a relatively balanced distribution of message strategies. Then two coders did a thorough discussion and established a set of comprehensive message decoding standards. Each coder decoded those 45 videos separately to identify the message strategy used in those videos. The discrepancies in the coding results were resolved through further discussion. Cohen's Kappa (κ) was adopted as an indicator of intercoder reliability. The final calculated average κ score of 0.87 across the six message strategies, indicates a relatively high level of agreement between the two coders.

After the decoding process, each of the 45 videos, referring to 45 different cosmetic products, was paired with a questionnaire containing 17 questions. The questionnaire aims to assess viewers' perceived risk in purchasing this product, the degree to which this product meets their personal needs, and their purchasing intention of this product after watching the video ad. Those measurements are conducted through a 5-point Likert scale. The first question identified whether the respondents had previously watched related video ads online to purchase cosmetic products for themselves or others, followed by five questions measuring consumer perceived risk (PR) adopted from S. Forsythe et al. (2006), Martin & Camarero (2009), Javadi et al. (2012), and Masoud (2013),

each addressing a different dimension of perceived risk defined in this study — financial risk, product risk, social risk, time risk, and information security risk. Five questions measuring personalization (P) and two questions measuring consumer purchasing intention (PI) were then developed from Srinivasan et al. (2002), Michaelidou & Hassan (2008), and C. Kim & Yang (2017). Additionally, four demographic questions were included at the end of the questionnaire, aiming to acquire information regarding the respondents' genders, ages, monthly dispensable incomes, and educational backgrounds. The survey was randomly distributed to online respondents through two different research platforms, Wenjuanwang and Credemo. A total of 592 respondents participated in this study, and then ineligible and incomplete responses were identified and removed. After that, to ensure a relatively balanced distribution of respondents across those 45 videos for regression analysis, redundant responses were randomly deleted, ensuring that each video contained 6 to 10 responses within the data set. After the filtering process, 196 responses were eliminated, leaving 386 valid and complete responses retained for further in-depth analysis.

IV. RESULTS

A. Descriptive Analysis and Reliability & Validity Check

As depicted in TABLE I, 386 valid responses were eventually kept for future investigation. In terms of demographics, the survey population was predominantly female (74.61%) and aged between 18 and 45 (92.48%), which approximates the customer composition of real-world cosmetic market (Krust, 2019; Yang, 2024). In addition, most respondents hold an undergraduate degree (77.98%) and have a monthly income of 5000 yuan or more (66.58%), indicating that they have a sufficient level of discretion and disposable income to differentiate and purchase cosmetic products online. Another descriptive analysis was conducted for the three measured variables in this study — perceived risk, personalization, and consumer purchasing intention — by calculating the average score and standard deviation across all items for each respondent. The result in TABLE II indicates that respondents generally reported medium perceived risk (mean = 2.577) but relatively high levels of personalization (mean = 3.662) and purchasing intention (mean = 3.921). Moreover, the distribution of perceived risk (standard deviation = 0.771) among respondents is narrower compared to personalization (standard deviation = 0.812) and purchasing intention (standard deviation = 0.990), indicating that the variation in perceived risk among them is less pronounced.

TABLE I. DEMOGRAPHICS OF RESPONDENTS

Statistic	Category	Frequency	Percentage (%)	Cum. Percentage (%)
<i>Gender</i>	Male	98	25.39	25.39
	Female	288	74.61	100.00
<i>Age</i>	Under 18	2	0.52	0.52
	18-30	183	47.41	47.93
	31-45	174	45.08	93.01

TABLE IV. MESSAGE STRATEGIES ADOPTED AND LENGTH OF SAMPLE VIDEOS

Statistic	Category	Frequency	Percentage(%)	Cum. Percentage (%)
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Statistic	Category	Frequency	Percentage (%)	Cum. Percentage (%)
<i>Education</i>	46 or above	27	6.99	100.00
	Junior high school or below	1	0.26	0.26
	Senior or technical high school	22	5.70	5.96
	Undergraduates	301	77.98	83.94
	Graduates or above	62	16.06	100.00
	1199 yuan or below	9	2.33	2.33
<i>Income</i>	1200-1999 yuan	41	10.62	12.95
	2000-2999 yuan	29	7.51	20.47
	3000-4999 yuan	60	15.54	36.01
	5000-9999 yuan	123	31.87	67.88
	10000 yuan or above	124	32.12	100.00

TABLE II. DESCRIPTIVE STATISTICS OF MEASURED VARIABLES

Variable	N	Mean	Standard Deviation
<i>Perceived Risk</i>	386	2.577	0.771
<i>Personalization</i>	386	3.662	0.812
<i>Consumer Purchasing Intention</i>	386	3.921	0.990

TABLE III and TABLE IV present an overview of the videos retained. Among those 45 sample videos, 42 (93.33%) employed a sensory strategy, which is consistent with the prominence of this approach in real-world cosmetic advertising. The remaining 5 message strategies appeared in 16 (35.56%) to 21 (46.67%) of those 45 videos, which satisfies the distribution requirements for effective analysis regarding their impacts on consumer purchasing intention. Notably, 37 (82.22%) videos incorporated 2-4 message strategies simultaneously, indicating the prevalence of message strategy combinations in these videos. Additionally, 27 (60%) of them had lengths of 30-89 seconds, aligning with the average TikTok video length of 42.7 seconds in 2024 (Ceci, 2024).

TABLE III. FREQUENCY OF SAMPLE VIDEOS ADOPTING CERTAIN MESSAGE STRATEGIES

Statistic	Category	Frequency	Percentage(%)
<i>Message Strategy Contained</i>	Ego	17	37.78%
	Social	19	42.22%
	Sensory	42	93.33%
	Routine	16	35.56%
	Acute Need	21	46.67%
	Rational	21	46.67%

<i>Number of Message Strategies Contained</i>	1	4	8.89	8.89
	2	12	26.67	35.56
	3	12	26.67	62.22
	4	13	28.89	91.11
	5	4	8.89	100.00
<i>Video Length</i>	0-29	12	26.67	26.67
	30-59	17	37.78	64.44
	60-89	10	22.22	86.67
	90-119	4	8.89	95.56
	120-149	1	2.22	97.78
	150-179	1	2.22	100.00

TABLE V. RELIABILITY CHECK FOR MEASURED VARIABLES

Variable	Abbreviation	Cronbach's α
<i>Perceived Risk</i>	PR	0.71
<i>Personalization</i>	P	0.83
<i>Consumer Purchasing Intention</i>	CPI	0.84

TABLE VI. VALIDITY CHECK FOR MEASURED VARIABLES

X^2/df	GFI	CFI	NFI	TLI	SRMR
2.427	0.947	0.962	0.938	0.951	0.053

A reliability check, summarized in TABLE V, was conducted on the three variables included in the questionnaire — perceived risk, personalization, and consumer purchasing intention — measured using a 5-point Likert scale. The Cronbach's α values for perceived risk, personalization, and consumer purchasing intention range between 0.71 and 0.84, indicating that the constructs used in this study have acceptable reliability (Fornell, 1981). A subsequent validity check was conducted for those three measured variables using six fit indices: X^2/df , GFI, CFI, NFI, TLI, and RMSEA. As shown in TABLE VI, the model's X^2/df is 2.427, RMSEA is 0.053, and the GFI, NFI, TLI, and SRMR all exceed 0.9, indicating acceptable structural validity.

B. Main Effect Test

To address H1–H4, a series of linear regressions were conducted by using SPSS27.0 to examine consumer purchasing intention in relation to a set of independent variables, including personalization, perceived risk, message strategies (MS), and their combinations. The results are summarized in TABLE VII. Here, MS refers to the total number of message strategies used in the video, with MS1 to MS6 representing individual message strategies, and MS1-2 to MS5-6 representing various combinations of strategies. In total, six individual message strategy segments and 15 combinations were tested.

Given the large number of independent variables and their high correlation, four distinct regressions were performed on different groups of variables to mitigate multicollinearity and enhance clarity. The results of Model 1 indicate that personalization ($\beta = 0.715$, $p < 0.001$) has a significant positive effect, while perceived risk ($\beta = -0.090$, $p < 0.05$) has a significant negative effect on consumer purchasing intention, thus supporting both H1 and H4. Specifically, when a video ad makes consumers feel that the advertised cosmetic product aligns with their preferences, the likelihood of

purchase increases. In contrast, if a consumer perceives high risk, their purchase intention decreases, though the impact is smaller and less significant compared to that of personalization. Models 2 and 3 were conducted subsequently but did not yield significant results, indicating that neither individual message strategies nor the number of strategies used in a cosmetic video ad significantly contribute to consumer purchasing intention. However, in Model 4, two specific message strategy combinations — “sensory + ration” ($\beta = 0.323$, $p < 0.01$) and “routine + ration” ($\beta = -0.328$, $p < 0.01$) — were found to have significant positive and negative impacts on consumer purchasing intention, respectively. These results suggest that when a cosmetic video ad combines sensory and ration strategies, consumers are more likely to purchase the advertised product, whereas the combination of routine and ration strategies has a detrimental effect on their purchasing intention.

C. Perceived Risk's Contributors and Moderating Effects

Another series of regression analyses, as shown in TABLE VIII, were conducted to examine the relationship between different message strategies (and their combinations) and perceived risk to address H5. Again, to reduce multicollinearity, three distinct models were analyzed: individual message strategies, the number of strategies applied, and message strategy combinations. The results of Models 1 and 2 indicate that neither individual message strategies nor the total number of strategies significantly influence consumer perceived risk. However, Model 3 reveals a significant negative impact of the “ego + routine” combination on perceived risk ($\beta = -0.162$, $p < 0.05$). This suggests that when a cosmetic video ad combines ego and routine strategies, consumers are more likely to perceive a higher risk of negative purchase outcomes. Consistent with previous findings that “ego + routine” does not directly influence purchasing intention, this result indicates that

perceived risk fully mediates their relationship, supporting H5.

To further test H6, PROCESS v4.2 was employed to examine the moderating effects of perceived risk on the relationships between two effective message strategy combinations — “sensory + ration” and “routine + ration” — and consumer purchasing intention. A similar analysis was conducted subsequently to test the effect of “perceived risk ×

personalization” on purchasing intention for H7. All dependent variables and moderators were mean-centered to mitigate multicollinearity. As depicted in TABLE IX, a significant moderating effect of perceived risk was identified in the relationship between personalization and consumer purchasing intention ($\beta = -0.161$, $p < 0.001$), which supports H7. However, H6 was rejected, as no significant moderating effect of perceived risk was found between the tested message strategy combinations and consumer purchasing intention.

TABLE VII. EFFECT OF PERSONALIZATION, PERCEIVED RISK, AND MESSAGE STRATEGIES ON CONSUMER PURCHASING INTENTION

Model	Variable	β (B)	VIF	R ² (%)
1	Personalization	0.715***	1.453	0.592
	Perceived Risk	-0.090*	1.453	
	MS1	-0.014	1.046	
	MS2	0.010	1.092	
2	MS3	0.026	1.179	0.011
	MS4	0.081	1.069	
	MS5	0.016	1.220	
	MS6	0.036	1.154	
3	MS	0.068	1.000	0.005
	MS1-2	0.093	3.093	
	MS1-3	-0.008	3.312	
	MS1-4	0.019	2.145	
4	MS1-5	0.025	2.685	0.050
	MS1-6	-0.125	3.501	
	MS2-3	-0.087	4.462	
	MS2-4	-0.068	3.951	
	MS2-5	-0.066	3.512	
	MS2-6	0.140	3.316	
	MS3-4	0.323**	4.601	
	MS3-5	0.116	3.534	
	MS3-6	0.189	3.971	
	MS4-5	-0.013	2.971	
	MS4-6	-0.328**	4.994	
	MS5-6	-0.089	2.873	

Statistical Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. MS1-MS6 represent ego, social, sensory, routine, acute need, and ration message strategy, respectively.

TABLE VIII. EFFECT OF MESSAGE STRATEGIES ON PERCEIVED RISK

Model	Variable	β (B)	VIF	R ² (%)
1	MS1	0.018	1.046	0.016
	MS2	-0.030	1.092	
	MS3	0.045	1.179	
	MS4	-0.057	1.069	
	MS5	-0.094	1.220	
	MS6	0.017	1.154	
2	MS	-0.053	1.000	0.003
	MS1-2	0.088	3.093	
	MS1-3	0.129	3.312	
3	MS1-4	-0.162*	2.145	0.016
	MS1-5	-0.054	2.685	
	MS1-6	0.056	3.501	
	MS2-3	0.102	4.462	

MS2-4	0.013	3.951	
MS2-5	-0.104	3.512	
MS2-6	-0.045	3.316	
MS3-4	-0.162	4.601	
MS3-5	-0.023	3.534	0.016
MS3-6	-0.080	3.971	
MS4-5	0.101	2.971	
MS4-6	0.197	4.994	
MS5-6	-0.016	2.873	

Statistical Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, MS1-MS6 represent ego, social, sensory, routine, acute need, and ration message strategy, respectively.

TABLE IX. MODERATING EFFECT ANALYSIS OF PERCEIVED RISK

Model	Relationship	β (B)	R ² (%)
1	PR $\times$ MS3-4 $\rightarrow$ CPI	0.120	0.247
2	PR $\times$ MS4-6 $\rightarrow$ CPI	0.022	0.240
3	PR $\times$ P $\rightarrow$ CPI	0.161***	0.604

Statistical Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, MS1-MS6 represent ego, social, sensory, routine, acute need, and ration message strategy, respectively.

V. DISCUSSION AND MANAGEMENT IMPLICATIONS

This study delves into the complex impacts of different message strategies (combinations) used in cosmetic short video advertisements on consumer purchasing intentions. The findings reveal that the “sensory + ration” strategy significantly enhances consumer purchasing intention. This suggests that, for cosmetic product users, simultaneously emphasizing the sensory appeal of the product and providing logical, rational explanations of its benefits can create a synergistic effect, thereby improving promotional outcomes. In contrast, the “routine + ration” strategy could decrease consumer interest when applied. Additionally, while the “ego + routine” strategy does not directly influence purchasing intention, it indirectly affects purchase decisions by increasing perceived risk. These findings indicate that when short videos present scenarios emphasizing convenience and daily use, cosmetic consumers resist overly detailed product analyses and descriptions. However, they may expect concise, compelling product highlights that address their concerns without requiring extensive analysis. Notably, our study found no significant effects of individual message strategies on purchasing intention, which further underscores the importance of strategic combinations. Therefore, content creators should avoid monotonous approaches and instead design rich, diverse content for customers that is both appealing in senses and persuasive in rationales. At the same time, since this study only focuses on the current Chinese digital cosmetic market, marketers should analyze consumer decision-making processes in-depth, and consider current market dynamics to formulate precise and effective strategies.

Additionally, consistent with prior research, this study reaffirms the central role of personalization and perceived risk in cosmetic marketing. Firstly, personalization has a significantly stronger positive influence on purchasing intention than the negative impact of perceived risk. What's more, when consumers perceive high purchasing risks, personalized promotions can more effectively enhance their willingness to purchase, which offsets the adverse effects of perceived risk. This highlights that, in cosmetic marketing, addressing consumers' personalized needs for specific products should take precedence over merely alleviating their concerns. With the increasingly sophisticated content recommendation mechanisms on Chinese short video

platforms, marketers should leverage the relevant technological advantages, such as big-data analysis, to accurately target potential customers. By conducting in-depth research regarding consumers' demographic factors (e.g., age, gender, income), behavioral data, and preferences, they can design product attributes tailored to the customer needs. Moreover, beyond the platform's embedded personalized recommendation system, marketers can harness the power of artificial intelligence within their own online stores to deliver more customized products and services suggestions at a relatively low cost. For example, AI-powered chatbots can respond to a high volume of customer inquiries in a personalized and timely manner, thereby enhancing the overall customer experience (Hardiansyah & Judijanto, 2025). This chatbot technology has already been applied on a small scale within China's WeChat Mini Programs and has a greater potential to be specifically trained for pre-sales consultation and after-sales services.

Secondly, this study also demonstrates the varied moderating effects of consumer perceived risk. Perceived risk is found to positively moderate the relationship between personalization and consumer purchasing intention, but has negligible moderating influence on the link between effective message strategy combinations and consumer purchasing intention. According to the risk-framing theory (Tversky & Kahneman, 1981), high perceived risk increases the effectiveness of loss-framed messages, but not gain-framed ones. Given that respondents reported moderate-to-high levels of perceived risk (mean = 2.577) in this study, cosmetic influencers may consider providing moderate information about the potential negative effects of not taking the products, rather than solely focusing on their advantages. Moreover, since this study found that perceived risk tends to be a relatively stable factor with less variation for cosmetic purchases, marketers cannot rely exclusively on message strategies to mitigate its negative effects. Instead, despite meeting the minimum requirement of providing a fixed amount of detailed product information or effects, they should also focus on building quality trust by enhancing transparency in production processes and displaying certification labels. Short video platforms can also play a pivotal role in building up customers' trust by streamlining and smoothing in-app purchasing processes, as well as implementing robust data

protection mechanisms. These platform-oriented measures can effectively reduce users' time risk and information security risk, which ultimately contributes to a more trustworthy purchasing environment.

VI. THEORETICAL CONTRIBUTIONS AND LIMITATIONS

This study offers several considerable scientific contributions. Firstly, it advances the growing body of literature on the effects of cosmetic short video advertisements. Rather than concentrating on specific attributes of video content (e.g., content richness, aesthetic quality, or brand trust), this study adopts a broader approach by analyzing video content through Taylor's six-segment message strategy wheel. This framework comprehensively encompasses almost all elements displayed in video advertisements, providing more holistic and practical insights. Furthermore, this study reaffirms the applicability of a traditional marketing model—Taylor's six-segment message strategy wheel—in the context of digital marketing research. It is also the first to employ this model in analyzing the combined effects of message strategies, thereby addressing a notable gap in the existing literature. Future research could build on this foundation by using both comprehensive and specific decoding methods to explore the effects of message strategies in diverse markets, or by developing modernized typologies that reflect the evolving nature of marketing content and promotional formats.

Secondly, while this study corroborates existing findings regarding the positive influence of personalization and the negative influence of perceived risk on consumer purchasing intention, it also contributes to the understanding of perceived risk's varied moderating effects. Previous research suggests that perceived risk can moderate the relationship between certain non-cognitive, emotionally driven factors (e.g., hedonic motivation, word-of-mouth, and consumer satisfaction) and consumer behaviors. However, when the dependent variable shifts to cognition-related factors (e.g., utilitarian motivation, attitude, and perceived usefulness), no moderating effect is typically observed (Jangir et al., 2022; Lavuri et al., 2022; Ozyer et al., 2014; v. Wangenheim & Bayón, 2004). In line with this reasoning, this study demonstrates that perceived risk moderates the relationship between personalization and consumer purchasing intention. Interestingly, it finds no moderating effect between perceived risk and the effectiveness of specific message strategy combinations, even for strategies targeting consumers from their ritual, rather than transmission view. One possible explanation is that message strategies, even though emotionally focused, are already designed to convey specific and concrete "benefits" and "functions" to customers. The risk-framing literature suggests that gain strategies and not as effective as loss strategies in high-risk environments, rendering their effects less susceptible to moderation by perceived risk (Tversky & Kahneman, 1981). Future studies could further validate this hypothesis by employing more systematic and structured approaches to test the moderating effects of perceived risk, such as testing whether the cognition-related factors are more aligned with "gains" in the context of risk framing. Such efforts would provide practical insights for marketers seeking to make more precise, risk-aware strategic decisions.

This study also acknowledges several limitations. Although it identifies several effective or detrimental message strategy combinations in the current Chinese cosmetic market, optimal strategies may vary over time and across different

market conditions. For marketers targeting other products, regions, or future scenarios, combining A/B testing with big data analytics could yield valuable insights (Villanova et al., 2021). By monitoring consumer responses to various strategy combinations (e.g., "sensory + rational" vs. "sensory + emotional") in real-time — using metrics such as view duration, click-through rates, and conversion rates — marketers can dynamically refine their promotional content. Additionally, due to time and budget constraints, this study relied on an existing, traditional, and well-established message typology — Taylor's six-segment message strategy wheel, and only divided the promotion contents into informational & emotional views. Nevertheless, it is essential to notice that, with the rise of social media, the promotional contents in short video marketing are often not limited to the products themselves as in traditional marketing. This development gives rise to a third category of message strategies: Interactional message strategies, which leverages the interactive nature of social media platforms to foster the two-way interaction between brands and customers, or between customers themselves, helping to build the brand culture and trust (Agrawal & Mittal, 2024; Tafesse & Wien, 2018; X. Wang et al., 2023). These indirect promotional efforts should also be considered in real-world cosmetic marketing, but beyond the scope of this paper. Finally, this study used newly created accounts to eliminate the influence of algorithmic personalization when collecting sample videos, ensuring a more standardized testing environment across the respondent group. In practice, however, consumers are continuously exposed to personalized recommendation algorithms while watching short videos, which makes this study's environment somewhat idealized. Therefore, marketers and influencers should take into account the built-in personalization systems when they apply the findings of this study to reality.

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