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# 자아표현과 조절초점이론의 상호작용: 인플루언서의 감정적 프레이밍이 판매 성과에 미치는 영향

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## 국문요약

본 연구는 인플루언서가 소셜 미디어 콘텐츠에서 나타내는 MBTI 기반의 성격 특성을 활용하여, 자아표현(self-representation)이 동기적 프레이밍(motivational framing)과 상호작용하여 판매 성과에 미치는 영향을 실증적으로 분석하였다. 특히, 동기 조절 초점 이론(Regulatory Focus Theory, RFT)을 기반으로 하여 촉진 초점(promotion-focused)과 예방 초점(prevention-focused) 메시지가 성격 기반의 콘텐츠 효과성에 어떠한 조절적 역할을 수행하는지 탐구하였다. 이를 위해 개별 게시물 수준에서 자아표현 전략의 차이를 분석한 결과, 감정형(F) 성격 특성을 지닌 인플루언서의 경우, 공감적이고 열망적인 커뮤니케이션과 강한 정합성을 보이는 촉진 초점의 정서적 메시지를 사용할 때 더 높은 판매 성과를 보이는 것으로 나타났다. 반면, 사고형(T) 성격 특성을 지닌 인플루언서는 논리적이고 객관적인 소통 방식과 잘 부합하는 예방 초점의 사실 기반 메시지를 활용할 때 더 우수한 판매 성과를 달성하는 것으로 밝혀졌다. 이러한 결과는 성격에 기반한 자아표현과 동기적 프레이밍을 전략적으로 결합할 때, 소비자의 참여를 촉진하고 실질적인 구매 행동을 유도하는 데 효과적임을 보여준다. 본 연구는 기존의 단순한 감정 분석(sentiment analysis)을 넘어 콘텐츠의 심리적 메커니즘과 역동을 깊이 있게 다룸으로써, 소셜 미디어에서 인플루언서의 자아표현과 동기적 메시지가 소비자 행동에 미치는 영향에 대한 이론적 이해와 실무적 활용 가능성을 발전시키는 데 기여한다.

주요어: MBTI, 자아표현, 동기 조절 초점 이론, 인플루언서 마케팅, 소셜미디어

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# The Interplay of Self-Representation and Regulatory Focus Theory: Influencers' Emotional Framing Impact on Sales

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## Abstract

This study investigates how influencers' self-representation—captured through MBTI-based personality traits expressed in social media content—interacts with motivational framing to affect sales performance. Drawing on Regulatory Focus Theory (RFT), it explores how promotion- versus prevention-focused messaging moderates the effectiveness of personality-driven content. By analyzing post-level variations in self-representation, the study shows that influencers with Feeling (F) traits achieve higher sales when using promotion-focused emotional appeals, reflecting their strength in empathetic and aspirational communication. In contrast, influencers with Thinking (T) traits perform better with prevention-focused, fact-based messaging, aligning with their logical and objective style. These findings underscore the strategic value of aligning personality expression with motivational framing to enhance consumer engagement and drive purchasing behavior. The research offers practical guidance for influencer marketing: F-type influencers should leverage emotionally resonant, promotion-oriented messages, while T-type influencers benefit from prevention-framed, informational content. By moving beyond basic sentiment analysis to uncover deeper psychological dynamics, this study advances understanding of how self-representation and motivation jointly influence digital commerce outcomes.

Key words: MBTI, Self-representation, Regulatory Focus Theory, Influencer marketing, Social media

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# Ⅰ. Introduction

Social media has significantly transformed not only personal communication and information sharing but also the broader business landscape. In particular, social commerce, driven by social media platforms, has rapidly accelerated the shift from traditional business-to-consumer (B2C) transaction models toward interactive, consumer-to-consumer (C2C) digital exchanges (Statista, 2024). The widespread adoption of social media has facilitated this transition, establishing itself as a central platform for novel forms of economic interaction. Within this context, influencer marketing has emerged as a key strategy that enables brands to engage more effectively with consumers. Specifically, personal recommendations provided by influencers are perceived as more authentic and trustworthy compared to conventional advertising, thus positively influencing consumers' purchase behaviors and decision-making processes (Influencer Marketing Hub, 2024).

Influencers are individuals who produce their own distinctive content on social media platforms, continuously interacting with followers and exerting significant influence. Often referred to as "social media celebrities," influencers effectively convey messages by cultivating emotional and personal relationships with their followers. Consequently, user-generated content (UGC) produced by influencers and other social media users has emerged as essential data for in-depth analysis of consumer behavior and emotions (Zhan et al., 2018; Stavrianea & Kavoura, 2015). Sentiment analysis, in particular, enables the evaluation of consumers' opinions, emotions, and attitudes as expressed in this content, providing clear insights into consumer responses toward brands or products (Ghiassi et al., 2016; Ceron & Negri, 2015). However, existing sentiment analysis research has predominantly focused on sentiment polarity—categorizing sentiments as positive, negative, or neutral—which limits its ability to fully capture consumers' underlying motivations and objectives behind their emotional expressions (Gonsalves, 2020; Mäkeläinen, 2021).

Furthermore, the extent to which influencers successfully build relationships with consumers depends significantly on how they represent themselves on social media and how this representation is perceived by followers. In other words, influencers strategically manage and adjust their self-presentation to project desired images intentionally to their audience (Hoose & Rosenbohm, 2024).

To overcome the limitations of existing sentiment analysis approaches, this study introduces Regulatory Focus Theory (RFT) to analyze emotional messages by categorizing them according to their motivational orientation: promotion-focused and prevention-focused. More specifically, the study explores how influencers' self-representation strategies interact with the motivational orientation of messages to impact sales performance. Thus, unlike traditional sentiment analysis, which emphasizes sentiment polarity, this study focuses on the psychological structures and motivational directionality behind emotional messages, seeking deeper insights. By applying RFT, the research aims to clarify the mechanisms that drive consumer responses and comprehensively explain how emotional message framing and influencers' strategic self-representation collectively shape consumer behavior and sales outcomes. Ultimately, this research is expected to significantly contribute to both theoretical understanding and practical applications in influencer marketing and digital commerce strategies.

# II. Literature Reviews

## 2.1 Self Representation in Influencer Marketing

Self-representation refers to the ways in which influencers express their identities, personalities (including MBTI-based traits), and values to their followers, thus building trust and fostering emotional bonds (Van Reijmersdal et al., 2024). Influencers employ various self-representation strategies depending on the type of relationship they aim to establish with their audience. The three primary strategies include the layperson strategy, the opinion leader strategy, and the micro-celebrity strategy. First, the layperson strategy involves influencers candidly sharing everyday life, including their imperfections or vulnerabilities, thereby enhancing intimacy and accessibility with followers. Previous studies have demonstrated that this layperson approach is most effective at creating strong emotional connections and securing high levels of trust from followers. Second, the opinion leader strategy positions influencers as authoritative and trusted sources by emphasizing their expertise and knowledge within specific fields. Lastly, the micro-celebrity strategy involves influencers adopting an image similar to traditional celebrities, highlighting their fame and exclusivity to enhance their appeal.

Although the effectiveness of these self-representation strategies can vary according to specific objectives, the layperson strategy, in particular, has proven most impactful in fostering emotional connections, thereby significantly enhancing follower engagement and consumer loyalty. Additionally, self-representation plays an essential role in the process of emotional contagion, defined as the phenomenon where one person's emotions influence and transfer to others (Wang et al., 2024). The influencer's self-representation serves as a cognitive framework through which followers perceive and interpret the influencer's emotions. In particular, authentic and relatable self-representation can facilitate positive emotional contagion, boosting followers' emotional engagement. This heightened emotional engagement subsequently contributes positively to brand trust and consumer behaviors.

Therefore, this study aims to empirically examine the effects of influencers' various self-representation strategies on actual sales performance.

## 2.2 Regulatory Focus Model

Sentiment analysis, defined as a computational method for evaluating individuals' opinions, attitudes, and emotional states through text data, has emerged as a key area of research in natural language processing (NLP) (Gangrade et al., 2019; Chan, 2023; Alam, 2022). Originally driven by academic curiosity, sentiment analysis has evolved into an essential tool for developing marketing strategies and optimizing communication by providing deep insights into consumer attitudes and behaviors (Rodríguez-Ibánez et al., 2023; Damle & Agarwal, 2020). For example, sentiment analysis is effectively utilized in influencer marketing by classifying the textual and emoji content of Instagram posts into positive, neutral, or negative sentiments, thereby enabling the assessment of campaign effectiveness and audience engagement (Zhan et al., 2018).

However, sentiment analysis primarily focuses on the polarity of emotions—positive, negative, or neutral—and thus often fails to capture the underlying intention or nuanced consumer responses behind the expressed sentiments (Kim & Yoo, 2012). For instance, a negatively toned message such as warnings or cautionary advice could, under certain contexts, positively influence consumer decision-making (Maheswaran & Meyers-Levy, 1990). This limitation highlights the need to consider not just sentiment polarity but also the motivational orientation and intent behind emotional messages.

In response to this limitation, Regulatory Focus Theory (RFT), proposed by Higgins (1997, 1998), provides a robust theoretical framework for categorizing emotional messages beyond mere sentiment polarity by focusing on motivational orientation. RFT differentiates between two primary motivational orientations—promotion focus and prevention focus—that significantly influence individuals' goal-setting, decision-making processes, and emotional experiences. Promotion-focused messages emphasize aspirations, accomplishments, and ideal outcomes, using optimistic and enthusiastic tones to stimulate consumer expectations. In contrast, prevention-focused messages prioritize safety, responsibility, and risk mitigation, employing cautious and realistic tones to promote consumer vigilance and protective behaviors (Förster, 2009).

Numerous studies have demonstrated the efficacy of RFT in explaining consumer emotions and behaviors. Brockner & Higgins (2001) revealed that individuals with a promotion focus experience emotions along a joy-dejection continuum, whereas prevention-focused individuals experience emotions along a calmness-anxiety continuum. Additionally, Pham & Avnet (2009) suggested that promotion-focused individuals prioritize emotional elements in decision-making, while prevention-focused individuals favor analytical thinking. Further empirical research has confirmed that promotion-focused messages effectively elevate consumer optimism and expectations for ideal outcomes, whereas prevention-focused messages enhance consumer trust and stability through a focus on safety and risk avoidance (Werth & Förster, 2007).

Given these theoretical insights, the current study aims to analyze how the interaction between influencer self-representation strategies and motivational framing (promotion vs. prevention focus) impacts consumer behaviors and actual sales performance.

## 2.3 MBTI based Self-representation and Motivational Framing

Self-representation typically refers to the manner in which individuals express their inherent personality traits, core values, and identities. However, in the dynamic and interactive environment of social media, self-representation becomes more flexible and context-dependent. Influencers, in particular, often strategically modify or enhance specific personality traits based not only on their genuine characteristics but also on the objectives, context, and messaging goals of the content they produce. Within this framework, the Myers-Briggs Type Indicator (MBTI) serves as an effective personality classification tool that influencers can strategically employ to guide their content creation. MBTI categorizes individuals according to preferred ways of processing information and making decisions, highlighting distinct differences especially within the dimensions of Feeling (F) and Thinking (T).

Individuals characterized by the Feeling (F) dimension typically prioritize empathy, emotional connection, and interpersonal harmony. Such individuals naturally gravitate toward promotion-focused messaging, which is designed to evoke positive emotions, optimism, aspirational goals, and the ideal outcomes audiences often desire. According to existing literature (Aaker & Lee, 2001; Isen, 2001; Pham & Avnet, 2004; Scholer & Higgins, 2012; Bagozzi et al., 1999), this alignment of personality traits and message content enhances emotional resonance and audience engagement. Consequently, influencers who strategically emphasize their Feeling-oriented traits through promotion-focused messages are more likely to build stronger emotional bonds with their audience, thereby significantly enhancing audience participation, consumer trust, and ultimately purchase intentions.

Conversely, individuals characterized by the Thinking (T) dimension tend to prefer logical, structured, analytical, and fact-based approaches to decision-making and communication. These influencers typically favor clear, objective, and evidence-supported content while avoiding overly emotional or subjective expressions. Consequently, Thinking-oriented personalities align closely with prevention-focused messaging, which emphasizes safety, caution, responsibility, risk avoidance, and practicality (Crowe & Higgins, 1997; Choi, 2018). Influencers who strategically highlight their Thinking-oriented traits through prevention-focused content provide their followers with reliable, factual, and detailed information, thus fostering higher credibility, enhancing audience trust, and encouraging rational decision-making among consumers.

The strategic alignment of specific personality dimensions (Feeling vs. Thinking) with corresponding motivational framing (promotion vs. prevention) significantly affects how consumers perceive and respond to social media content. Specifically, the effective combination of Feeling traits with promotion-focused messaging can amplify emotional engagement and enhance consumer attitudes toward products and brands, positively influencing purchase behaviors. Conversely, the strategic pairing of Thinking traits with prevention-focused messages strengthens the delivery of clear, factual, and practical information, effectively guiding consumers' rational decision-making processes and fostering deeper trust and brand credibility.

Given these considerations, strategically integrating MBTI-based self-representation strategies with appropriate motivational message framing emerges as a critical factor for maximizing influencer effectiveness and driving successful marketing outcomes. Therefore, this study aims to empirically investigate how the interaction between MBTI-based influencer self-representation (Feeling vs. Thinking) and motivational framing (promotion vs. prevention) influences actual sales performance. By exploring these relationships, the study seeks to provide valuable insights into optimal content strategies, ultimately enhancing both theoretical understanding and practical implications for influencer marketing and social media-based consumer engagement.

# III. Data and Method

## 3.1 Data

This study examines data derived from 332 influencers who collaborated with an influencer marketing agency between August 2018 and May 2020. These influencers promoted various brands and products through their social media platforms, with sales performance data tracked via the agency's database. Image and video data from influencers' social media accounts were also collected to analyze the number of people featured in each image, which serves as a moderating variable in the dynamics between influencers.

Instagram, as a visually dominant social media platform, stands apart from text-focused platforms due to its emphasis on visual content, which has notable implications for user engagement and psychological impact (Fardouly et al., 2020; Tiggemann et al., 2018; Chatzopoulou et al., 2020).

This study utilizes a comprehensive dataset combining social media activities and sales performance data collected from influencers' Instagram accounts and an influencer marketing agency. A total of 664,161 records of social media content were gathered, encompassing images, videos, comments, replies, likes, hashtags, and emoji counts. The sales data, obtained from the influencer marketing agency, includes detailed information on promotional events, such as event names, start and end dates, as well as product details, including categories (e.g., food, beauty, fashion), prices, and quantities sold.

Content data for this study were collected from Instagram, with a focus on captions where motivational directionality and self-representation are most prominently expressed. While Instagram allows hashtags and textual content to appear in both captions and comments, this study emphasizes captions as the primary vehicle for influencers' self-representation and motivational messaging. By analyzing captions, the research captures the intentional alignment between personality traits, motivational focus (promotion vs. prevention), and content strategy, avoiding potential confounding effects from follower-generated content in the comment section.

The dataset includes textual content, regulatory focus classification, and sales performance metrics provided by the influencer marketing agency. Regulatory focus classification was conducted on the captions to categorize posts as promotion-focused or prevention-focused, enabling a nuanced investigation of the alignment between influencers' motivational messaging and their MBTI personality traits, particularly the Feeling (F) and Thinking (T) types. Sales performance, measured as the total revenue generated during a campaign, serves as the dependent variable, linking personality-motivation fit to tangible marketing outcomes.

The data analysis involved multiple steps to process and classify the motivational focus of influencer captions effectively. First, captions were preprocessed using KoBERT's tokenizer, which breaks down sentences into tokens suitable for analysis. Once preprocessed, the tokenized captions were fed into the fine-tuned KoBERT model, which classified each caption as either promotion-focused or prevention-focused. The classification was based on probability scores for each category, with the highest probability determining the final label. For example, a caption might yield scores of [0.75 (promotion-focused), 0.25 (prevention-focused)], resulting in a classification of "promotion-focused."

This application of KoBERT enables the study to transcend traditional sentiment analysis by focusing on regulatory focus classification. By employing a model fine-tuned for motivational framing, the research identifies how influencers strategically align their messaging with their self-representation. This classification provides critical insights into the interplay between regulatory focus, messaging strategies, and sales performance, thereby offering a comprehensive understanding of influencer marketing dynamics.

Following outlines the key variables used in the analysis, categorized into dependent, independent, and control variables. Each variable is defined and contextualized within the framework of the study. The correlation matrix displaying the correlations among variables is presented in 〈Table 1〉.

## 3.2 MBTI

In this study, to operationalize MBTI personality types as measurable variables, each influencer's MBTI type was extracted by comprehensively analyzing their seven-day social media posts (written in Korean). The MBTI classification framework, grounded in Carl Jung's typological theories, categorizes individuals into 16 distinct personality types based on four dichotomous dimensions. This study utilized the MBTI framework to analyze

〈Table 1〉 Correlation Matrix

Correlation Matrix

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | 1.0000 | | | | | | | | | | | | | | | | | |
| (2) | -0.0015 | 1.0000 | | | | | | | | | | | | | | | | |
| (3) | 0.1215 | -0.0758 | 1.0000 | | | | | | | | | | | | | | | |
| (4) | -0.0583 | 0.4910 | -0.2058 | 1.0000 | | | | | | | | | | | | | | |
| (5) | -0.0760 | -0.0976 | -0.2083 | 0.6205 | 1.0000 | | | | | | | | | | | | | |
| (6) | -0.0193 | 0.2190 | -0.1811 | 0.8191 | 0.7378 | 1.0000 | | | | | | | | | | | | |
| (7) | -0.1728 | 0.0724 | -0.1468 | 0.2048 | 0.1375 | 0.1111 | 1.0000 | | | | | | | | | | | |
| (8) | -0.0359 | -0.0601 | -0.2554 | 0.0309 | 0.0698 | 0.0372 | 0.0243 | 1.0000 | | | | | | | | | | |
| (9) | -0.0263 | -0.0882 | -0.1489 | -0.0390 | -0.0142 | -0.0320 | -0.2015 | 0.4054 | 1.0000 | | | | | | | | | |
| (10) | -0.0041 | -0.0233 | 0.0175 | -0.0624 | -0.0561 | -0.0668 | -0.0929 | 0.0609 | 0.3530 | 1.0000 | | | | | | | | |
| (11) | -0.0552 | -0.0066 | 0.0371 | -0.0573 | -0.0919 | -0.0906 | 0.1893 | 0.0885 | 0.1394 | 0.0158 | 1.0000 | | | | | | | |
| (12) | 0.1396 | -0.1092 | 0.5855 | -0.1708 | -0.1023 | -0.1202 | -0.2783 | -0.1324 | -0.0514 | 0.0521 | -0.1794 | 1.0000 | | | | | | |
| (13) | 0.1886 | -0.0965 | -0.2789 | -0.0751 | -0.0520 | -0.1129 | -0.1813 | 0.3513 | 0.3039 | 0.1092 | -0.0400 | -0.1762 | 1.0000 | | | | | |
| (14) | 0.1251 | -0.0850 | 0.5263 | -0.1211 | -0.0966 | -0.0712 | -0.3704 | -0.0301 | 0.0519 | 0.0971 | -0.0492 | 0.7010 | -0.0109 | 1.0000 | | | | |
| (15) | 0.0810 | -0.0793 | -0.3731 | -0.0805 | -0.0642 | -0.0531 | -0.1155 | -0.0264 | 0.0117 | 0.0707 | -0.0878 | 0.4046 | 0.0970 | 0.5429 | 1.0000 | | | |
| (16) | 0.0542 | -0.1670 | -0.2442 | -0.0620 | 0.0348 | -0.0507 | -0.1230 | 0.4768 | -0.3876 | 0.0956 | 0.2966 | -0.1731 | 0.4504 | 0.0326 | 0.0267 | 1.0000 | | |
| (17) | 0.1540 | -0.0634 | 0.2740 | 0.0353 | 0.0510 | 0.0176 | 0.0172 | -0.0614 | 0.1010 | 0.0770 | 0.0132 | 0.1786 | -0.1035 | 0.1218 | 0.0826 | -0.1144 | 1.0000 | |
| (18) | 0.0912 | -0.1034 | 0.1015 | -0.0581 | 0.0245 | -0.0184 | -0.3525 | -0.1298 | -0.1154 | -0.0235 | -0.0681 | 0.0523 | -0.0629 | 0.0091 | -0.0237 | -0.1798 | 0.0989 | 1.0000 |

*(1) ln (sales)$_{it}$ (2) F_mbti$_{it}$, (3) Promotion$_{it}$, (4) I_mbti$_{it}$, (5) N_mbti$_{it}$, (6) J_mbti$_{it}$, (7) Mbti_Mismatch$_{it}$ (8) Emoji_Count$_{it}$, (9) User_Tags_Receive$_{it}$, (10) Influencer_Tag_Sent$_{it}$, (11) Hashtag_Count$_{it}$, (12) Post_Count$_{it}$, (13) Follower Comments it' (14) Image$_{it}$, (15) video$_{it}$, (16) Influencer_Reply_Length$_{it}$, (17) Account_Age$_{i}$, (18) Campaign_Incentive$_{it}$*

and classify each influencer's personality type according to their social media content. The MBTI classification model was trained using a dataset provided by Kaggle, derived from the PersonalityCafe forum, which includes discussions and posts related to MBTI personality types. For English-language posts, textual data were vectorized using tools such as TfidfVectorizer or CountVectorizer, transforming text into numerical representations based on word frequency. Subsequently, a Gaussian Naive Bayes (GaussianNB) classifier was trained on these vectorized data, enabling the prediction of MBTI types based on the probabilities of word occurrences.

Once classified, MBTI types were converted into binary variables for quantitative analysis, with each dimension represented as a separate binary indicator. For instance, the dimensions were coded as follows: "I" as 1 and "E" as 0; "N" as 1 and "S" as 0; "F" as 1 and "T" as 0; and "J" as 1 and "P" as 0. This methodological approach ensured a systematic and accurate extraction of MBTI personality types from the data, facilitating their inclusion in subsequent analyses.

## 3.3 Regulatory Focus

This study utilized KoBERT, a deep learning model optimized for Korean language processing, to analyze the motivational framing and emotional directionality of influencer-generated social media content. Specifically, the KoBERT model was fine-tuned according to Regulatory Focus Theory (RFT) to classify influencer captions into promotion-focused or prevention-focused messages. For instance, in the context of influencer marketing, content intended for product promotion should not be inherently interpreted as negative; rather, all content should be understood as strategically designed to motivate consumer purchase behavior. Even messages that superficially appear negative typically align with prevention-focused messaging, which explicitly acknowledges consumer concerns or potential risks while emphasizing stability, reliability, and long-term benefits.

Additionally, it is rare for influencers to present a purely negative statement such as, "This product is not good," without immediately following up with a contrasting phrase like "however," thereby ultimately emphasizing the positive attributes of the product. A representative example would be, "This feature may not be ideal, but the advantages significantly outweigh it." This structure aligns closely with prevention-focused strategies within RFT, which acknowledge potential drawbacks while simultaneously reinforcing overall trust and stability, thereby boosting consumer trust and encouraging purchase intentions.

Supporting this perspective, Li et al. (2021) demonstrated that negatively framed messages, emphasizing the risks of inaction (e.g., highlighting problems that may arise from neglecting health checkups), were more effective in promoting consumer behaviors such as purchasing recycled products compared to positively framed messages. In other words, messages perceived as superficially negative often align strategically with prevention-focused messaging, underscoring the importance of taking action and positively influencing consumer behavior. Similarly, Yousef et al. (2021) pointed out that negative appeals, which are used in over 70% of social advertisements, effectively stimulate behavior changes by creating emotional discomfort. Though these negative appeals initially evoke discomfort, they ultimately reinforce prevention-focused strategies by emphasizing the critical importance and benefits of products or actions.

Considering these theoretical insights alongside practical contexts, this study clearly recognizes that all influencer-generated content, irrespective of its superficial tone, fundamentally aims at promoting products and driving sales. Messages highlighting potential risks or drawbacks should thus be understood as components of prevention-focused strategies, ultimately emphasizing product value, fostering consumer trust, and encouraging consumer actions.

This methodological approach enables the current study to more precisely capture the connection between motivational framing inherent in the content and the strategic self-representation of influencers. By leveraging a fine-tuned model consistent with RFT principles, this research bridges the gap between linguistic analysis and theoretical frameworks, offering deeper insights into how regulatory focus influences actual sales.

## 3.4 OLS

This study defines a unique unit of analysis as the "Influencer-Event" pair to explore the relationship between influencer self-representation, emotional sentiment, and sales outcomes. An "event" refers to a seven-day period of influencer activities associated with the promotion of a specific sentiment-aligned campaign. Consequently, each observation in the dataset represents an independent combination of an influencer and their promotional efforts over a seven-day period, enabling granular and detailed analysis of sales performance.

To empirically examine the relationship among influencers' self-representation strategies, motivational framing, and actual sales performance, the study utilizes a panel data regression model. The dependent variable, Log_sales, represents log-transformed sales figures to address issues of skewness and potential outliers in the data. Key independent variables include F_mbti, a binary variable capturing the Feeling personality trait characterized by empathy and emotional sensitivity, and Promotion, a continuous variable measuring the frequency of promotion-focused messaging that highlights aspirations, optimism, and personal achievements. The interaction term between F_mbti and Promotion evaluates the combined effect of empathetic personality traits and promotion-focused messaging, emphasizing their joint influence on sales performance.

Additionally, T_mbti, a binary variable representing the Thinking trait characterized by logic, analytical orientation, and objectivity, is incorporated alongside Prevention, a continuous variable reflecting the frequency of prevention-focused messaging emphasizing caution, responsibility, and risk avoidance. The interaction term between T_mbti and Prevention assesses the combined effect of logical personality traits and prevention-focused messaging, specifically examining their joint impact on consumer trust and subsequent sales outcomes.

To strengthen the validity of the analysis, the regression model includes several control variables. Personality-related controls include additional MBTI dimensions such as J_mbti, N_mbti, and I_mbti, as well as Mbti_Mismatch, which captures potential discrepancies between an influencer's self-represented personality and the brand's ideal personality profile. Social media engagement metrics, including Emoji_Count (the number of emojis used), User_Tags_Received (the number of follower-generated tags), Influencer_Tags_Sent (the number of tags influencers themselves used), Follower_Comments (the number of comments followers posted), Influencer_Reply_Length (the average length of influencer replies), and

Hashtag_Count, were incorporated to reflect the intensity of interaction and visibility of the content. Content-related variables, such as Post_count (the total number of posts during the event) and the number of images and videos shared, were also controlled to account for variations in content volume and format. Lastly, account and campaign-specific characteristics, including Account_Age (duration since the influencer's account was established) and Campaign_Incentive (presence of campaign-related incentives), were controlled to ensure the analysis accounted for historical and contextual influences on sales. The regression equation is specified as follows:

$$\ln{(sales)_{it}} = \beta_0 + \beta_1 F\_mbti_{it'} + \beta_2 Promotion_{it'} + \beta_3 (F\_mbti \times Promotion)_{it'} + X_{it'}\beta + \alpha_i + \lambda_t + \varepsilon_{it}$$

The dependent variable, ln(sales)it, represents the log-transformed sales generated by influencer $i$ during event $t$. To examine how influencer personality traits and motivational messaging jointly impact sales, the model incorporates key personality variables and motivational focus measures.

Specifically, the independent variables include F_mbtiit, and T_mbtiit, binary indicators of the influencer's Feeling and Thinking traits, respectively, derived from posts made during the seven days preceding event t. Additionally, the model includes continuous variables, Promotionit and Prevention it, measuring the frequency of promotion-focused and prevention-focused posts, respectively, over the same seven-day period. Interaction terms (F_mbti×Promotion)it and (T_mbti×Prevention)it capture how the alignment between Feeling or Thinking traits and their respective motivational message framing affects sales. A comprehensive set of control variables Xit is included to account for additional influencer characteristics, social media activity, and campaign dynamics. These controls encompass other MBTI personality traits (Introversion (I), Sensing (S), Judging (J)), Mbti_Mismatch (to measure alignment with brand-preferred personality traits), social media engagement metrics (Emoji_Count, User_Tags_Received, Influencer_Tags_Sent, Follower_Comments, Influencer_Reply_Length, and

Hashtag_Count), content-related variables (Post_count, number of images and videos posted), and campaign-related variables (Account_Age, Campaign_Incentive). Their effects are represented by coefficients$\beta$. Influencer-specific fixed effects ($\gamma i$) are also incorporated to control for time-invariant individual attributes, such as personal style or baseline audience engagement. Additionally, time-specific fixed effects ($\delta t$) represented by dummy variables for each event year—are included to address unobserved factors such as seasonality, macroeconomic conditions, and annual trends. Finally, the error term ($\varepsilon it$) captures idiosyncratic influences on sales performance. Overall, this integrated model provides a robust framework for understanding the nuanced interactions between influencers' self-representation, motivational framing, and sales effectiveness.

# Ⅳ. Results

The analysis results confirmed that the alignment between personality-based self-representation and motivational framing plays a significant role in influencing sales performance within influencer marketing (See 〈Table 2〉 & 〈Table 3〉).

Specifically, influencers characterized by the Feeling (F) type demonstrated higher sales performance when utilizing promotion-focused messaging. This finding highlights the strong synergy created by combining the empathetic and emotionally expressive self-representation of F-type influencers with promotion-focused messages that emphasize hope, aspirations, and personal achievements. Promotion-focused messaging enhances the F-type influencer's inherent ability to emotionally connect with and build trust among their audience, resulting in increased content resonance and persuasive impact. Consequently, this alignment not only boosts follower engagement but also effectively translates into actual consumer purchase behavior.

Conversely, influencers with the Thinking (T) personality type achieved greater sales outcomes when employing prevention-focused messaging. This result indicates that the logical, objective self-representation of T-type influencers aligns powerfully with prevention-focused messages that emphasize caution, responsibility, and risk avoidance, maximizing content credibility and persuasiveness. Although T-type influencers excel at logical, data-driven communication, their effectiveness diminishes if they adopt overly aspirational or emotionally oriented promotion-focused messaging. Such misalignment can reduce audience trust, undermine the influencer's credibility, and ultimately weaken the effectiveness of their content in driving sales performance.

These findings underscore the critical importance of strategic alignment between motivational framing and influencer self-representation in marketing campaigns. Feeling (F)-type influencers can maximize sales performance by leveraging their strengths in emotional engagement through promotion-focused content, while Thinking (T)-type influencers achieve optimal results by maintaining logical, objective communication via prevention-focused messaging. Ultimately, these insights emphasize the necessity for influencers to strategically incorporate their personality traits into content development, enabling effective maximization of marketing outcomes.

〈Table 2〉 Result of F_mbti with Promotion-focused Messages

| ln_sales | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| F_mbti with Promotion-focused Messages | | | 1.3093*** (0.4877) |
| F_mbti | | -.2896 (0.8705) | -2.7743** (1.2526) |
| Promotion-focused Messages | 0.1470 (0.3722) | | -0.3504 (0.4041) |
| J_mbti | -1.2178 (0.7605) | -1.0735 (0.7908) | -1.1272 (0.7776) |
| N_mbti | 0.1167 (0.7743) | -0.0129 (0.8724) | -0.7244 (0.8831) |
| I_mbti | 1.5751* (0.8514) | 1.6554* (0.9444) | 2.5319** (0.9733) |
| Mbti_Mismatch | -0.3479 | -0.3923 | -0.3740 |

| | | | |
|---|---|---|---|
| | (0.3420) | (0.3447) | (0.3372) |
| Emoji_Count | 0.0164<br>(0.1162) | 0.0071<br>(0.1199) | -0.0351<br>(0.1168) |
| User_Tags_Received | 0.0342<br>(0.1629) | 0.0430<br>(0.1645) | 0.1410<br>(0.1631) |
| Influencer_Tags_Sent | -0.0987<br>(0.3480) | -0.1145<br>(0.3486) | -0.2863<br>(0.3436) |
| Hashtag_Count | -0.2980<br>(0.6214) | -0.2252<br>(0.6311) | 0.2072<br>(0.6375) |
| Post_Count | 0.0146<br>(0.0395) | 0.0179<br>(0.0389) | 0.0590<br>(0.0415) |
| Follower_ Comments | 0.4581<br>(0.5162) | 0.3946<br>(0.5246) | -0.0383<br>(0.5387) |
| Image | 0.1997<br>(0.5012) | 0.2620<br>(0.4498) | 0.0204<br>(0.4960) |
| Video | -0.2232<br>(0.3010) | -0.2467<br>(0.3009) | -0.5423*<br>(0.3142) |
| Influencer_Reply_Length | 0.6301<br>(0.6036) | 0.6921<br>(0.6397) | 1.0821*<br>(0.6342) |
| Account_Age | -0.2297<br>(0.9073) | -0.3761<br>(0.8742) | -0.7723<br>(0.9042) |
| Campaign_Incentive | 0.8186<br>(0.5127) | 0.7769<br>(0.5110) | 0.5696<br>(0.5050) |
| Time Fixed Effected | Yes | Yes | Yes |
| R-squared | 0.3102 | 0.3063 | 0.3910 |
| Obs. | 1,109 | 1,109 | 1,109 |
| Robust standard errors in parentheses<br>***p<0.01, **p<0.05, *p<0.1 | | | |

〈Table 3〉 Result of T_mbti with Prevention-focused Messages

| ln_sales | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| T_mbti with Prevention-focused Messages | | | -2.6113**<br>(1.2439) |
| T_mbti | | -0.4162<br>(0.8980) | 0.5285<br>(0.7329) |
| Prevention-focused Messages | 0.5470<br>(0.6935) | | 1.5425***<br>(0.5031) |
| J_mbti | -0.1741*<br>(0.0773) | 0.2799<br>(0.2725) | -0.9969<br>(0.7732) |
| N_mbti | -1.3416<br>(.7450) | 0.0917<br>(0.2253) | -0.1165<br>(0.9600) |
| I_mbti | -0.1412<br>(0.8071) | 0.6308**<br>(0.2475) | 1.9513*<br>(1.0487) |
| Mbti_Mismatch | -0.0025 | -0.0027 | -0.4403 |

| | | | |
|---|---|---|---|
| | (0.0055) | (0.0055) | (0.3499) |
| Emoji_Count | 2.0955**<br>(0.8630) | -0.0226<br>(0.0178) | -0.5429<br>(0.6459) |
| User_Tags_Received | -0.6046<br>(0.3464) | -0.0113<br>(0.1364) | 0.1260<br>(.1612) |
| Influencer_Tags_Sent | 0.0000<br>(0.0010) | -0.0000<br>(0.0010) | -0.2349<br>(0.3394) |
| Hashtag_Count | 0.0182<br>(0.3650) | 0.0072<br>(0.0095) | 0.3331<br>(0.6322) |
| Post_Count | 0.0000<br>(0.0000) | 0.0000<br>(0.0000) | 0.0378<br>(.0442) |
| Follower_ Comments | -0.0076<br>(.118613) | 0.3537***<br>(0.0974) | -0.3854<br>(0.5574) |
| Image | -0.0456<br>(0.1571) | 0.0837<br>(0.1292) | -0.0568<br>(0.4947) |
| Video | -1.2663<br>(1.5298) | -1.4666<br>(1.5364) | -0.5901*<br>(0.3168) |
| Influencer_Reply_Length | 0.1416<br>(0.1453) | 0.1887<br>(0.1445) | 1.4409**<br>(0.6253) |
| Account_Age | 0.1256<br>(0.3871) | 0.1826<br>(0.3875) | -1.2074<br>(0.9069) |
| Campaign_Incentive | 0.8058<br>0.5170 | 0.7358<br>0.5163 | 0.5841<br>0.5029 |
| Time Fixed Effected | Yes | Yes | Yes |
| R-squared | 0.3102 | 0.3063 | 0.3910 |
| Obs. | 1,109 | 1,109 | 1,109 |
| Robust standard errors in parentheses<br>***p<0.01, **p<0.05, *p<0.1 | | | |

# V. Robustness Check

To ensure the robustness of the baseline findings, a subsample analysis focusing on nano-influencers was conducted. Nano-influencers, defined by Himelboim & Golan (2023) as individuals with 1,000 to 50,000 followers, represent a unique segment of influencers characterized by smaller but highly engaged audiences. Within the dataset of 332 influencers, 185 were identified as nano-influencers, accounting for 780 events out of the total 1,109 events in the full dataset.

The panel data regression analysis on this subsample confirmed the validity of the key findings from the full sample (refer to 〈Table 4〉 & 〈Table 5〉).

Specifically, Hypothesis 1 was supported, as nano-influencers with Feeling (F) personality traits demonstrated higher sales performance when their posts aligned with promotion-focused messaging. Similarly, Hypothesis 2 was also validated within this subsample, showing that Thinking (T) nano-influencers generated higher sales when their posts adopted prevention-focused messaging.

This additional layer of analysis underscores the generalizability of the results across different influencer segments. Despite their smaller follower base, nano-influencers exhibited the same dynamics between personality-driven self-representation and motivational framing fit, reinforcing the study's conclusions. The robustness check not only bolsters confidence in the overall findings but also highlights the relevance of these dynamics in contexts where personalized and trust-driven interactions play an even greater role in influencing consumer behavior.

〈Table 4〉 Robustness Check Result of F_mbti with Promotion-focused Messages

| ln_sales | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| F_mbti with Promotion-focused Messages | | | 1.3625***<br>(0.5027) |
| F_mbti | | -0.3178<br>(0.8854) | -2.9380**<br>(1.2915) |
| Promotion-focused Messages | 0.2005<br>(0.3937) | | -0.3693<br>(0.4331) |
| J_mbti | -1.2526<br>(0.7700) | -1.0820<br>(0.7993) | -1.1443<br>(0.7838) |
| N_mbti | 0.0964<br>(0.7867) | -0.0420<br>(0.8828) | -0.7717<br>(0.8911) |
| I_mbti | 1.6234*<br>(0.8612) | 1.6954*<br>(0.9563) | 2.6290**<br>(0.9851) |
| Mbti_Mismatch | -0.3187<br>(0.3488) | -0.3755<br>(0.3521) | -0.3733<br>(0.3439) |
| Emoji_Count | 0.0405<br>(0.1230) | 0.0301<br>(0.1273) | -0.0207<br>(0.1239) |
| User_Tags_Received | 0.0295<br>(0.1646) | 0.0391<br>(0.1663) | 0.1402<br>(0.1644) |
| Influencer_Tags_Sent | -0.1227<br>(0.3522) | -0.1406<br>(0.3530) | -0.3173<br>(0.3469) |

| | | | |
|---|---|---|---|
| Hashtag_Count | -0.3063<br>(0.6294) | -0.2178<br>(0.6381) | 0.2323<br>(0.6455) |
| Post_Count | 0.0174<br>(0.0402) | 0.02208<br>(0.0395) | 0.0660<br>(0.0426) |
| Follower_ Comments | 0.4122<br>(0.5256) | 0.3424<br>(0.5342) | -0.0892<br>(0.5449) |
| image | 0.1222<br>(0.5193) | 0.2078<br>(0.4703) | -0.0914<br>(0.5152) |
| video | -0.2279<br>(0.3040) | -0.2555<br>(0.3045) | -0.5636*<br>(0.3179) |
| Influencer_Reply_Length | 0.6568<br>(0.6182) | 0.7211<br>(0.6583) | 1.1584*<br>(0.6529) |
| Account_Age | -0.1422<br>(0.9215) | -0.3236<br>(0.8919) | -0.7389<br>(0.9193) |
| Campaign_Incentive | 0.8618<br>(0.5200) | 0.8080<br>(0.5184) | 0.5820<br>(0.5125) |
| Time Fixed Effected | Yes | Yes | Yes |
| R-squared | 0.3171 | 0.3158 | 0.3847 |
| Obs. | 780 | 780 | 780 |
| Robust standard errors in parentheses<br>***p<0.01, **p<0.05, *p<0.1 | | | |

〈Table 5〉 Robustness Check Result of T_mbti with Prevention-focused Messages

| ln_sales | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| T_mbti with Prevention-focused Messages | | | -1.5936***<br>(0.5270) |
| T_mbti | | -0.3178<br>(0.8854) | 2.6860**<br>(1.2962) |
| Prevention-focused Messages | 0.3178<br>(0.8854) | | 2.0618**<br>(0.9116) |
| J_mbti | -1.0820<br>(0.7993) | -1.0820<br>(0.7993) | -1.0357<br>(0.7827) |
| N_mbti | -0.0420<br>(0.8828) | -0.0420<br>(0.8828) | -0.2223<br>(0.9713) |
| I_mbti | 1.6954*<br>(0.9563) | 1.6954*<br>(0.9563) | 2.0266*<br>(1.0724) |
| Mbti_Mismatch | -0.3755<br>(0.3521) | -0.3755<br>(0.3521) | -0.3611<br>(0.3418) |
| Emoji_Count | 0.0301<br>(0.1273) | 0.0301<br>(0.1273) | -0.0270<br>(0.1231) |
| User_Tags_Received | 0.0391<br>(0.1663) | 0.0391<br>(0.1663) | 0.1144<br>(0.1644) |
| Influencer_Tags_Sent | -0.1406<br>(0.3530) | -0.1406<br>(0.3530) | -0.2667<br>(0.3466) |

| | | | |
|---|---|---|---|
| Hashtag_Count | -0.2178<br>(0.6381) | -0.2178<br>(0.6381) | 0.3707<br>(0.6492) |
| Post_Count | 0.0220<br>(0.0395) | 0.0220<br>(0.0395) | 0.0447<br>(0.0452) |
| Follower_ Comments | 0.3424<br>(0.5342) | 0.3424<br>(0.5342) | -0.4071<br>(0.5886) |
| image | 0.2078<br>(0.4703) | 0.2078<br>(0.4703) | -0.0917<br>(0.5119) |
| video | -0.2555<br>(0.3045) | -0.2555<br>(0.3045) | -0.6397*<br>(0.3206) |
| Influencer_Reply_Length | 0.7211<br>(0.6583) | 0.7211<br>(0.6583) | 1.2863*<br>(0.6553) |
| Account_Age | -0.3236<br>(0.8919) | -0.3236<br>(0.8919) | -1.0024<br>(0.9332) |
| Campaign_Incentive | 0.8080<br>(0.5184) | 0.8080<br>(0.5184) | 0.6329<br>(0.5105) |
| Time Fixed Effected | Yes | Yes | Yes |
| R-squared | 0.3171 | 0.3158 | 0.3847 |
| Obs. | 780 | 780 | 780 |
| Robust standard errors in parentheses<br>***p<0.01, **p<0.05, *p<0.1 | | | |

# VI. Conclusion and Discussion

This study underscores the importance of aligning self-representation with motivational framing in influencer marketing. The findings provide strong empirical support for the hypotheses that Feeling (F) types achieve higher sales when their posts are promotion-focused, while Thinking (T) types generate higher sales when their posts are prevention-focused. These results highlight the pivotal role of personality-driven self-representation and its interaction with motivational framing in shaping consumer engagement and sales outcomes.

For influencers with Feeling (F) traits, their natural ability to foster emotional and aspirational connections with their audience amplifies the impact of promotion-focused messaging. Posts that align with their empathetic and emotionally expressive self-representation resonate deeply with followers, enhancing trust and relatability. This alignment allows F types to effectively leverage promotion-focused messaging to drive higher sales, reaffirming the importance of fit between personality and motivational framing in influencer marketing.

Conversely, the results for Thinking (T) types reveal the effectiveness of prevention-focused messaging that aligns with their logical and objective self-representation. Followers of T types tend to value fact-based, analytical communication, and content emphasizing caution, responsibility, and practicality strengthens their credibility. This alignment ensures that T types maintain audience trust and engagement, leveraging prevention-focused messaging to achieve stronger sales performance. The risks of misalignment are particularly evident when promotion-focused messaging clashes with the T type's rational self-representation, potentially diluting their credibility and reducing the effectiveness of their posts.

The robustness check further validates these insights, demonstrating that the dynamics observed in the full sample hold true for nano-influencers as well. This consistency across influencer segments highlights the generalizability of the findings and reinforces the importance of self-representation and motivational framing fit in driving sales performance, regardless of audience size.

In conclusion, this study contributes to the growing literature on influencer marketing by emphasizing the interplay between personality, motivational framing, and consumer behavior. The findings offer actionable insights for influencers and brands, suggesting that tailoring content strategies to align with influencers' personality traits and motivational focus can enhance authenticity, trust, and sales outcomes. For Feeling (F) types, leveraging promotion-focused messaging is a strategic advantage, while Thinking (T) types should prioritize prevention-focused communication to maintain their credibility. These insights pave the way for more personalized and effective influencer marketing strategies, where the alignment between self-representation and motivational framing becomes a key determinant of success.

For Feeling (F) type influencers, brands should focus on maximizing the motivational and emotional impact of their messaging. Collaborations with F type influencers are most effective when the content emphasizes promotion-focused messaging, including aspirational themes and emotional storytelling. Brands can encourage these influencers to share uplifting narratives, personal experiences, and emotionally resonant stories that align with their empathetic and expressive self-representation. By leveraging the F type's natural ability to create emotional and aspirational connections, campaigns can foster deeper audience engagement and drive stronger sales outcomes.

Conversely, Thinking (T) type influencers should be supported in creating content that aligns with their logical and fact-based communication style. Instead of emphasizing aspirational themes, brands should collaborate with T type influencers to deliver content that highlights caution, practicality, and reliability. Campaigns targeting T types' audiences should prioritize clarity, credibility, and functional value, ensuring the content resonates with their followers' expectations for rational and objective information.

The aspirational resonance of F type influencers' promotion-focused posts strengthens the emotional bond between influencers and their followers. This enhanced connection translates directly into increased trust and, ultimately, sales. To capitalize on this dynamic, brands should encourage F type influencers to share personal anecdotes or heartfelt stories that resonate emotionally with their audiences. These efforts not only enhance engagement but also deepen the sense of authenticity and relatability, fostering long-term loyalty among followers.

For T type influencers, maintaining credibility through logical and informational content is critical for sustaining audience trust. Followers of T types often expect rational, data-driven communication and may perceive overly aspirational messaging as inconsistent with the influencer's self-representation. To manage these expectations effectively, brands should collaborate with T type influencers to craft campaigns that emphasize facts, clear messaging, and functional benefits.

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