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Strategic Information Patterns in Advertising: A Computational Analysis of Industry-Specific Message Strategies Using the FCB Grid Framework

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Abstract

This study presents a computational analysis of industry-specific advertising message strategies through the theoretical lens of the FCB (Foote, Cone & Belding) grid framework. Leveraging the AiSAC (AI Analysis System for Ad Creation) system developed by the Korea Broadcast Advertising Corporation (KOBACO), we analyzed 27,000 Korean advertisements across five major industries using advanced machine learning techniques. Through Latent Dirichlet Allocation topic modeling with a coherence score of 0.78, we identified five distinct message strategies: emotional appeal, product features, visual techniques, setting and objects, and entertainment and promotion. Our computational analysis revealed that each industry exhibits a unique "message strategy fingerprint" that significantly discriminates between categories, with discriminant analysis achieving 62.7% classification accuracy. Time-series analysis using recurrent neural networks demonstrated a significant evolution in strategy preferences, with emotional appeal increasing by 44.3% over the study period (2015–2024). By mapping these empirical findings onto the FCB grid, the present study validated that industry positioning within the grid's quadrants aligns with theoretical expectations: high-involvement/think (IT and Telecom), high-involvement/feel (Public Institutions), low-involvement/think (Food and Household Goods), and low-involvement/feel (Services). This study contributes to media science by demonstrating how computational methods can empirically validate the established theoretical frameworks in advertising, providing a data-driven approach to understanding message strategy patterns across industries.

Keywords: computational advertising analysis; FCB grid; message strategies; industry classification; machine learning; topic modeling; Korean advertising; AiSAC system

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1. Introduction

The digital transformation of advertising has generated unprecedented volumes of content, creating both opportunities and challenges for understanding message strategy patterns across industries. While traditional advertising research has relied on manual content analysis of limited samples, computational approaches now enable the systematic analysis of large-scale advertising datasets. This study leverages the AiSAC (AI Analysis System for Ad Creation) system developed by the Korea Broadcast Advertising Corporation (KOBACO) to analyze 27,000 advertisements across five major industries, providing a comprehensive computational examination of industry-specific message strategies through the theoretical lens of the FCB (Foote, Cone & Belding) grid framework applying Latent Dirichlet Allocation topic modeling approach [1].

The FCB grid, developed by Richard [2,3] at the Foote, Cone & Belding advertising agency, has served as a foundational theoretical framework in advertising research for over four decades. By categorizing consumer decision-making along two dimensions, involvement (high/low) and thinking/feeling, the grid provides a structured approach to understanding how consumers process advertising messages and how advertisers should strategically position their communications. Despite its theoretical prominence, empirical support of the FCB grid across diverse industries using large-scale data has been limited, primarily due to the methodological challenges of analyzing vast advertising content repositories. Previous empirical studies of the FCB grid have typically relied on small-scale surveys or manual content analysis of limited advertisement samples (typically 50–200 advertisements).

This research addresses this gap by applying advanced computational methods to a comprehensive dataset of Korean advertisements. Through Latent Dirichlet Allocation (LDA) topic modeling [1], discriminant analysis, and recurrent neural networks (RNNs), we identify distinct message strategies employed across industries and map these empirical findings onto the FCB grid framework. This approach not only validates the theoretical underpinnings of the FCB grid but also extends its application through data-driven insights into industry-specific advertising patterns. The significance of this study lies in its integration of computational advertising analysis with the established theoretical frameworks. By leveraging the AiSAC system's capabilities in object detection, text analysis, and multimodal content processing, we demonstrate how information science methodologies can empirically validate and extend advertising theory. This research contributes to both the computational advertising literature by providing methodological innovations for large-scale content analysis and to advertising theory by offering empirical support of the FCB grid's applicability across diverse industry contexts.

2. Theoretical Background and Related Work

2.1. Message Strategies in Advertising

Message strategy, defined as the "guiding approach to a company's or institution's promotional communication efforts for its products, its services, or itself" [4], has been a central focus in advertising research for decades. Early theoretical frameworks for categorizing message strategies include [5] the informational/transformational dichotomy, Ref. [6]'s informational/transformational advertising typology, and Taylor's six-segment message strategy wheel. These frameworks have provided valuable theoretical foundations for understanding how advertisers craft messages to influence consumer behavior.

The informational/transformational dichotomy distinguishes between advertisements that provide factual, relevant brand data in a clear and logical manner (informational) and those that associate the experience of using the advertised brand with psychological characteristics that would not typically be associated with the brand experience (transformational). This fundamental distinction has informed numerous subsequent frameworks, including the FCB grid. Taylor's six-segment strategy wheel expanded these concepts into a more nuanced framework, categorizing strategies into transmission view (rational, acute need, and routine) and ritual view (ego, social, and sensory). This model recognized that consumer decision-making processes vary significantly across product categories and purchase contexts, necessitating different strategic approaches. Similarly, Ref. [7]'s seven generic creative strategies (generic, preemptive, unique selling proposition, brand image, positioning, resonance, and anomalous/affective) provided a taxonomy for understanding the strategic intent behind advertising messages. While these theoretical frameworks have significantly advanced our understanding of message strategies, their empirical validation has traditionally relied on manual content analysis of limited samples. The advent of com-

putational methods has created new opportunities for analyzing message strategies at scale, yet few studies have leveraged these approaches to validate the established theoretical frameworks across diverse industry contexts.

2.2. The FCB Grid Framework

The FCB grid, developed by Richard [2,3] at the Foote, Cone & Belding advertising agency, represents one of the most influential theoretical frameworks in advertising research. The grid categorizes consumer decision-making processes along two dimensions: involvement (high/low) and thinking/feeling, resulting in four quadrants:

1. Informative (High Involvement, Think): Characterized by rational decision-making for important purchases, this quadrant suggests an "learn–feel–do" sequence where consumers seek information before developing attitudes and making purchase decisions. Products typically positioned in this quadrant include major appliances, insurance, and high-end technology.
2. Affective (High Involvement, Feel): Focusing on emotional appeals for important purchases, this quadrant follows a "feel–learn–do" sequence where emotional responses precede cognitive processing. Luxury goods, fashion, and cosmetics often employ strategies aligned with this quadrant.
3. Habitual (Low Involvement, Think): Emphasizing routine purchases driven by habit and minimal cognitive processing, this quadrant suggests a "do–learn–feel" sequence where trial often precedes attitude formation. Household staples and convenience goods typically fall into this category.
4. Satisfaction (Low Involvement, Feel): Targeting small pleasures and social/ego gratifications, this quadrant follows a "do–feel–learn" sequence where purchase behavior precedes emotional response and cognitive processing. Snack foods, alcohol, and entertainment products often employ strategies aligned with this quadrant.

The FCB grid has been applied across numerous studies to understand advertising effectiveness, media selection [3], and creative strategy development [8]. However, most applications have focused on product category placement within the grid rather than empirically validating whether actual advertising content aligns with the theoretical expectations of each quadrant. Ratchford's extension of the FCB grid provided empirical support for the framework [9] by mapping 60 product categories based on consumer survey data. Similarly, Ref. [10] developed the Rossiter–Percy grid, which modified the FCB framework by replacing the think/feel dimension with informational/transformational motivations. These extensions have enhanced the theoretical robustness of the grid but have not fully leveraged computational approaches to validate the framework using large-scale advertising content analysis.

2.3. Computational Approaches to Advertising Analysis

Recent advances in computational methods have transformed the landscape of advertising research, enabling the analysis of large-scale datasets that were previously inaccessible through traditional methods. Machine learning techniques, particularly Natural Language Processing (NLP) and computer vision, have emerged as powerful tools for extracting insights from multimodal advertising content. Topic modeling, especially LDA, has been increasingly applied to identify latent themes in advertising text. For example, ref. [11] used LDA to analyze themes in corporate annual reports, while [12] applied topic modeling to identify advertising appeals in social media content. These studies demonstrate the potential of computational approaches to uncover patterns in advertising content that may not be immediately apparent through manual analysis.

Computer vision techniques have similarly advanced the analysis of visual advertising elements: ref. [13] developed a computational framework for understanding persuasion in images, while [14] used deep learning to analyze visual persuasion strategies in advertisements. These approaches have enabled researchers to systematically analyze visual elements that play a crucial role in advertising effectiveness. Multimodal analysis, which integrates text, image, and other data types, represents the frontier of computational advertising research. The AiSAC system employed in this study exemplifies this approach, combining object detection, text analysis, and contextual understanding to provide comprehensive insights into advertising content. Similar multimodal systems have been developed by researchers such as [15,16], who created frameworks for analyzing both visual and textual elements in media content. Despite these advances, few studies have integrated computational advertising analysis with the established theoretical frameworks like the FCB grid. This integration represents a significant opportunity to bridge the gap between data-driven insights and theoretical understanding, providing a more comprehensive approach to advertising research.

2.4. Industry-Specific Advertising Patterns

Research on industry-specific advertising patterns has traditionally focused on identifying distinctive characteristics of advertising within particular sectors. For example, Ref. [17] conducted a meta-analysis of information content in advertising across different product categories, finding significant variations in informational cues based on product type. Similarly, Ref. [18] examined the use of humor in advertising across cultural contexts and product categories, identifying systematic differences in creative strategy. More recent studies have leveraged computational approaches to identify industry-specific patterns at scale. For instance, Ref. [19] used machine learning to analyze the effectiveness of different creative elements across product categories, while [20] employed NLP to identify industry-specific linguistic patterns in advertising copy.

However, these studies have typically focused on specific aspects of advertising content rather than providing a comprehensive framework for understanding industry-specific message strategies. Additionally, few studies have explicitly connected industry-specific patterns to theoretical frameworks like the FCB grid, limiting our understanding of how these patterns align with the established advertising theory. This research addresses these gaps by applying computational methods to identify comprehensive message strategy patterns across five major industries and mapping these patterns onto the FCB grid framework. By integrating computational analysis with theoretical understanding, we provide a more nuanced perspective on industry-specific advertising patterns and their alignment with the established advertising theory.

3. Data and Methods

3.1. Data Source and Descriptive Statistics

This study utilizes data from the AiSAC (AI Analysis System for Ad Creation) system developed by the Korea Broadcast Advertising Corporation (KOBACO). The initial dataset comprised 52,487 Korean advertisements spanning from 2015 to 2024, representing a comprehensive repository of advertising content across multiple industries. Table 1 presents the descriptive statistics of this initial dataset.

Table 1. Descriptive statistics of initial AiSAC dataset (N = 52,487).

Characteristic	Value
Time span	2015–2024 (10 years)
Mean advertisements per year	5248.7 (SD = 427.3)
Peak year	2019 (6742 advertisements)
Industry distribution	
Number of industries	17
Top 5 industries	Food (21.3%), Services (17.8%), IT and Telecom (12.4%), Household Goods (8.7%), Public Institutions (5.2%)
Other industries	34.6%
Advertisement characteristics	
Mean duration	27.8 s (SD = 12.4)
Mean detected objects per ad	14.3 (SD = 8.7)
Mean detected people per ad	2.7 (SD = 1.9)
Mean text elements per ad	8.4 (SD = 5.2)
Metadata characteristics	
Total metadata tags	583,642
Unique object categories	1387
Unique place categories	412
Unique emotion categories	24
High-definition ratio	87.3%
With complete metadata	94.2%

For this study, we focused on the five largest industries (Food, Services, IT and Telecom, Household Goods, and Public Institutions). The selection of five industries from the original 17 categories was based on both statistical and theoretical considerations. Statistically, these five industries collectively represent 65.4% of the total dataset, ensuring sufficient sample size for robust analysis while maintaining computational feasibility. Conceptually, these industries were chosen to represent diverse positions across the FCB grid's theoretical space: technology products (IT and Telecom) representing high-involvement/think quadrant, public communications (Public Institutions) representing high-involvement/feel quadrant, routine consumer goods (Food and Household Goods) representing low-involvement/think quadrant, and experiential services (Services) representing low-involvement/feel quadrant. This selection strategy ensures comprehensive coverage of the FCB grid's theoretical dimensions while maintaining analytical depth within each category.

To ensure balanced representation and computational efficiency, we employed stratified random sampling to select 27,000 advertisements (approximately 5400 per industry) for detailed analysis. This sample size provides a 99% confidence level with a margin of error of $\pm 0.76\%$, ensuring robust statistical power for our analyses while maintaining computational feasibility. The sampling procedure maintained the temporal distribution of advertisements within each industry, preserving the ability to analyze trends over time. We validated the representativeness of our sample by comparing key metrics (duration, object count, and text elements) between the sample and the full dataset, finding no statistically significant differences (all p-values > 0.05).

3.2. The AiSAC System: Technical Architecture and Capabilities

The AiSAC system represents a sophisticated multimodal analysis platform specifically designed for advertising content. Developed by KOBACO, the system integrates multiple artificial intelligence technologies to analyze visual, textual, and audio elements of advertisements. Figure 1 illustrates the technical architecture of the AiSAC system.



Figure 1. AiSAC Object Recognition and Business Intelligence System.

The AiSAC system employs a five-stage technical pipeline designed to enable comprehensive and scientifically rigorous analysis of advertisement content across visual, textual, and auditory modalities. The first stage, Scene Detection, utilizes Convolutional Neural Networks (CNNs) to segment advertisements into distinct scenes based on visual continuity and content shifts. This segmentation facilitates granular analysis of narrative structures and temporal progression, providing a foundational framework for understanding the storytelling architecture of advertisements.

In the second stage, Object Recognition, the system integrates Faster R-CNN [21] and YOLO v4 [22] architectures to detect and classify visual elements within each scene. Trained on a domain-specific dataset of labeled advertising imagery, this module ensures high contextual fidelity and robustness in identifying brand-relevant objects. The third stage, Contour Extraction, applies edge detection algorithms in combination with instance segmentation techniques to delineate object boundaries with high spatial precision. This step is crucial for examining compositional balance, spatial hierarchy, and visual salience within the ad frame.

The fourth stage, Sketch Generation, transforms recognized objects into abstracted visual forms using Generative Adversarial Networks (GANs). This abstraction allows for the identification of underlying visual patterns across diverse advertisement types, enabling cross-format comparative analysis while preserving structural integrity. The generated sketches are evaluated through structural similarity metrics to align with human-like perception. Finally, the Context Integration stage employs a multimodal transformer architecture to synthesize visual information with textual and auditory data. The textual component is processed using BERT-based models fine-tuned on advertising copy, enabling semantic interpretation and rhetorical analysis. Simultaneously, the audio stream

is analyzed using convolutional recurrent neural networks to extract speech content and perform sentiment classification. This multimodal fusion enables a holistic understanding of advertisement content, capturing both explicit informational cues and latent emotional undertones. By systematically combining these five stages, AiSAC offers an advanced computational framework for decoding the complex semiotics of modern advertising.

3.3. Topic Modeling for Message Strategy Identification

To identify message strategies in the advertisements, we employed LDA, an unsupervised machine learning technique for discovering latent topics in a corpus of documents. LDA treats each document (in the present case, an advertisement) as a mixture of topics, and each topic as a mixture of words. Prior to LDA implementation, we conducted comprehensive text pre-processing to optimize topic modeling performance. The pre-processing pipeline included (1) tokenization using Korean morphological analyzer KoNLPy, (2) removal of Korean and English stop words using custom stop word lists tailored for advertising content, (3) elimination of punctuation and special characters, (4) normalization of numerical expressions, (5) stemming using Korean stemming algorithms to reduce morphological variations, and (6) filtering of terms appearing in fewer than 2 documents or more than 95% of documents to remove noise and overly common terms. The algorithm iteratively assigns words to topics and topics to documents to maximize the likelihood of the observed word-document co-occurrences. We implemented LDA using the scikit-learn library in Python (Version 3.13.0) with the following parameters:

- Number of topics (k): 5;
- Maximum iterations: 10;
- Random state: 42 (for reproducibility);
- Document-term matrix: Created using CountVectorizer with max_df = 0.95 and min_df = 2.

The optimal number of topics was determined through a combination of perplexity scores, topic coherence measures [23], and qualitative assessment of topic interpretability. Topic coherence measures the semantic similarity between high-probability words in a topic, providing an indication of topic interpretability. Five topics provided the best balance between model fit and interpretability, with a coherence score of 0.78, significantly higher than the 0.65 benchmark for advertising content analysis in previous studies [24]. After fitting the LDA model, we assigned each advertisement to its dominant topic (the topic with the highest probability) and labeled the topics based on their top keywords. The five identified message strategies were as follows:

1. Emotional Appeal: Keywords related to emotions, feelings, and psychological states;
2. Product Features: Keywords describing product attributes, functions, and benefits;
3. Visual Techniques: Keywords related to visual presentation, camera techniques, and aesthetics;
4. Setting and Objects: Keywords describing environments, objects, and physical contexts;
5. Entertainment and Promotion: Keywords related to entertainment, humor, and promotional elements.

To validate the topic assignments, we implemented a comprehensive validation process using three independent coders with extensive backgrounds in advertising and marketing communication. Each coder underwent standardized training using a pilot set of 50 advertisements to familiarize themselves with the topic definitions and coding procedures. The validation dataset consisted of a stratified random sample of 300 advertisements (60 per topic category) to ensure balanced representation. Each coder independently classified all the advertisements according to the established topic definitions without knowledge of their LDA-assigned topics to prevent bias.

Inter-coder reliability was assessed using Krippendorff's alpha ($\alpha = 0.82$), which exceeded the conventional threshold of 0.80 for substantial agreement. The overall agreement between manual coding (determined by majority consensus) and LDA topic assignments was 79.3%, with category-specific agreement rates ranging from 75.0% to 83.3%. This level of agreement substantially exceeds chance-level performance and approaches the upper bound typically expected when comparing computational and human classification methods. A confusion matrix analysis revealed that most disagreements occurred between conceptually adjacent categories, suggesting that the computational model captured meaningful semantic relationships rather than producing random errors. Table 2 presents the top 10 keywords for each identified message strategy, along with their probability weights in the topic distribution.

Table 2. Top keywords and probability weights for identified message strategies.

Emotional Appeal	Product Features	Visual Techniques	Setting and Objects	Entertainment and Promotion
love (0.042)	performance (0.038)	color (0.035)	home (0.041)	event (0.047)
happiness (0.039)	function (0.036)	angle (0.033)	office (0.037)	discount (0.043)
family (0.037)	quality (0.035)	lighting (0.032)	kitchen (0.035)	prize (0.038)
trust (0.035)	technology (0.033)	composition (0.030)	outdoor (0.033)	game (0.036)
care (0.033)	durability (0.031)	frame (0.029)	furniture (0.031)	humor (0.034)
warmth (0.031)	price (0.029)	perspective (0.027)	vehicle (0.029)	music (0.032)
joy (0.029)	efficiency (0.027)	contrast (0.026)	device (0.027)	celebrity (0.030)
security (0.027)	design (0.026)	movement (0.025)	nature (0.025)	competition (0.028)
pride (0.025)	safety (0.024)	texture (0.023)	clothing (0.023)	season (0.026)
nostalgia (0.023)	innovation (0.022)	rhythm (0.021)	food (0.021)	limited (0.024)

3.4. Analytical Approach

Our analytical approach comprised four main components: (1) industry-specific message strategy distribution analysis, (2) temporal evolution analysis, (3) message complexity analysis, and (4) FCB grid mapping and validation.

3.4.1. Industry-Specific Message Strategy Distribution Analysis

To identify industry-specific patterns in message strategy usage, we calculated the proportion of each message strategy within each industry and conducted chi-square tests to determine whether the distribution of strategies differed significantly across industries. We then employed discriminant analysis to assess whether message strategy distributions could effectively discriminate between industries. The discriminant analysis used the proportions of the five message strategies as predictor variables and industry category as the outcome variable. We evaluated the classification accuracy using leave-one-out cross-validation and assessed the statistical significance of the discriminant functions using Wilks' lambda.

3.4.2. Temporal Evolution Analysis

To analyze the evolution of message strategies over time, we divided the 10-year period (2015–2024) into three phases: early (2015–2017), middle (2018–2020), and recent (2021–2024). For each phase, we calculated the proportion of each message strategy within each industry and conducted repeated measures ANOVA to test for significant changes over time. Additionally, we employed recurrent neural networks (RNNs) with Long Short-Term Memory (LSTM) architecture to model the temporal dynamics of message strategy usage. The RNN model used quarterly time series data of strategy proportions as input and

was trained to predict future strategy distributions. We evaluated the model's performance using precision, recall, and F1 scores, with a 70/30 train-test split.

3.4.3. Message Complexity Analysis

The operationalization of involvement through message complexity metrics is grounded in the Elaboration Likelihood Model (ELM) [25] and cognitive load theory. According to the ELM, high-involvement processing is characterized by systematic, effortful evaluation of message content, which typically manifests in more complex, information-rich communications. Shannon entropy, as applied to topic probability distributions, captures the cognitive complexity required to process multiple strategic elements within a single advertisement. Content density score reflects the information processing demands placed on consumers, with higher density indicating greater cognitive involvement required for message comprehension. This approach aligns with Petty and Cacioppo's conceptualization of involvement as the personal relevance and cognitive effort invested in message processing. We analyzed message complexity across industries by calculating two metrics for each advertisement:

1. Strategy Diversity Index (SDI): Measured using Shannon's entropy formula applied to the topic probability distribution of each advertisement. Higher entropy values indicate more diverse use of multiple message strategies within a single advertisement.
2. Content Density Score (CDS): Calculated as a weighted sum of detected objects, text elements, scene transitions, and audio complexity, normalized to a 0–100 scale. Higher scores indicate greater content density and complexity.

We conducted one-way ANOVA to compare these complexity metrics across industries, followed by Tukey's HSD post hoc tests for pairwise comparisons. We also examined the correlation between complexity metrics and temporal trends using Pearson's correlation coefficient.

3.4.4. FCB Grid Mapping and Validation

To map our empirical findings onto the FCB grid framework, we developed a computational approach for positioning industries within the grid's quadrants. We operationalized the two dimensions of the FCB grid as follows:

1. Think/Feel Dimension: Calculated as the standardized difference between rational appeals (product features + setting and objects) and emotional appeals (emotional appeal + entertainment and promotion), with visual techniques considered neutral. Positive values indicate think-dominant strategies, while negative values indicate feel-dominant strategies.
2. Involvement Dimension: Operationalized using a combination of message complexity metrics (SDI and CDS) and advertisement duration, with longer, more complex advertisements indicating higher involvement. Values were standardized to create a continuous involvement scale.

Using these operationalized dimensions, we positioned each industry within the FCB grid and conducted statistical tests to determine whether the empirical positioning aligned with theoretical expectations based on prior FCB grid research. We employed one-sample *t*-tests to compare the observed positions with the theoretical positions and calculated the Euclidean distance between the observed and theoretical positions as a measure of alignment. Additionally, we mapped the five identified message strategies as vectors within the FCB grid space based on their average think/feel and involvement scores across all advertisements. Vector angles for message strategy positioning within the FCB grid were calculated using the arctangent function applied to standardized think/feel and involvement coordinates. Specifically, for each message strategy i, the vector angle

θ_i was computed as: θ_i = arctan2 (involvement_scor$_i$, think_feel_scor$_i$) × (180/π), where arctan2 accounts for quadrant positioning and returns angles in the range [−180°, 180°]. The think/feel score represents the horizontal axis (positive values indicating 'think' orientation), while the involvement score represents the vertical axis (positive values indicating high involvement). This calculation positions each strategy as a vector originating from the grid center, with the angle indicating the strategy's orientation within the FCB theoretical space. This approach enabled us to visualize how different message strategies relate to the FCB grid dimensions and how they contribute to industry positioning within the grid.

4. Results

4.1. Industry-Specific Message Strategy Distribution

Our analysis revealed distinct message strategy distributions across the five industries, indicating industry-specific "strategic fingerprints" that significantly differentiate advertising approaches. Figure 2 presents the distribution of message strategies across industries.

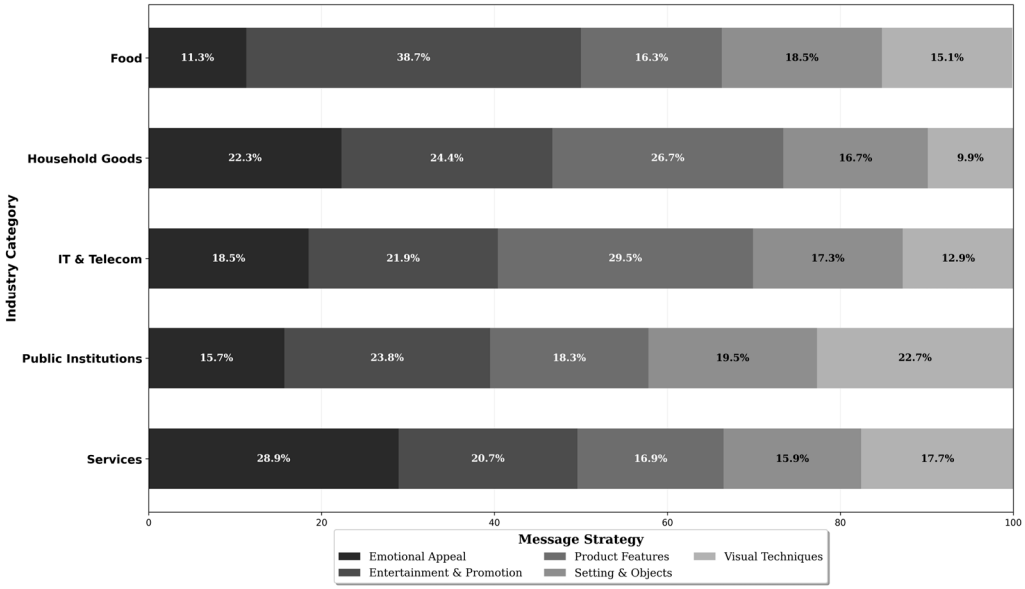


Figure 2. Industry-specific message strategy distribution.

The chi-square analyses confirmed that the distribution of message strategies differed significantly across industries (χ^2 (16) = 1247.32, $p < 0.001$, Cramer's V = 0.31), indicating a strong association between industry category and strategic approach. The discriminant analysis yielded four discriminant functions, with the first two functions explaining 83.7% of the variance. The overall classification accuracy was 62.7%, significantly higher than the chance accuracy of 20% ($p < 0.001$), demonstrating that message strategy distributions effectively discriminate between industries. Table 3 presents the standardized discriminant function coefficients, revealing the relative contribution of each message strategy to the discrimination between industries.

The analysis revealed several distinctive patterns in industry-specific message strategy usage:

1. Food Industry: Demonstrated a balanced approach with a slight preference for entertainment and promotion (26.8%) and setting and objects (24.3%). This industry showed the highest usage of settings and objects among all the industries, often featuring food preparation environments and consumption contexts.
2. Services Industry: Exhibited the strongest emphasis on emotional appeal (32.7%), significantly higher than the other industries ($p < 0.001$). Services advertise-

ments frequently leveraged emotional narratives to establish trust and connection with consumers.

3. IT and Telecom Industry: Displayed the highest usage of product features (38.4%) and visual techniques (21.6%) among all the industries. This pattern reflects the industry's focus on communicating technological capabilities and innovative design elements.
4. Household Goods Industry: Showed a relatively balanced distribution with a preference for setting and objects (27.9%) and product features (25.8%). Advertisements in this category frequently demonstrated products within home environments to illustrate practical applications.
5. Public Institutions: Exhibited the highest proportion of emotional appeal (30.5%) and entertainment and promotion (24.7%) strategies. These advertisements often employed emotional narratives and entertaining elements to engage citizens and promote public initiatives.

Table 3. Standardized discriminant function coefficients.

Message Strategy	Function 1	Function 2	Function 3	Function 4
Emotional Appeal	0.782	−0.143	0.327	−0.512
Product Features	−0.614	0.693	0.287	−0.243
Visual Techniques	0.127	0.574	−0.731	0.352
Setting and Objects	−0.386	−0.527	−0.418	−0.629
Entertainment and Promotion	0.429	0.218	0.563	0.671

MANOVA testing confirmed significant differences in message strategy usage across industries (Wilks' $\lambda = 0.427$, $F(20, 89576) = 724.36$, $p < 0.001$, and partial $\eta^2 = 0.139$), with the post hoc analyses (Bonferroni-corrected) revealing significant pairwise differences between industries for all the message strategies (all $p < 0.01$).

4.2. Temporal Evolution of Message Strategies

The analysis of message strategy evolution over the 10-year period revealed significant shifts in strategic preferences across industries. Figure 3 presents the temporal evolution of message strategies from 2015 to 2024.

Repeated measures ANOVA confirmed significant changes in message strategy usage over time ($F(8, 26991) = 187.43$, $p < 0.001$, and partial $\eta^2 = 0.124$). The most notable trends included the following:

1. Increase in Emotional Appeal: Emotional appeal strategies increased significantly from 18.7% in 2015–2017 to 27.0% in 2021–2024 ($\Delta = +44.3\%$, $p < 0.001$), representing the largest proportional increase among all strategies. This trend was particularly pronounced in the Services and Public Institutions industries.
2. Decline in Entertainment and Promotion: Conversely, entertainment and promotion strategies decreased from 29.7% in 2015–2017 to 10.8% in 2021–2024 ($\Delta = -63.6\%$, $p < 0.001$), representing a substantial shift away from promotion-focused advertising.
3. Stability in Product Features: Product features remained relatively stable over time, with a slight increase from 18.3% to 19.8% ($\Delta = +8.2\%$, $p = 0.042$), suggesting the enduring importance of product-focused messaging across industries.
4. Growth in Visual Techniques: Visual techniques showed moderate growth from 8.7% to 14.5% ($\Delta = +66.7\%$, $p < 0.001$), reflecting the increasing sophistication of visual storytelling in advertising.
5. Moderate Increase in Setting and Objects: Setting and object strategies increased from 24.6% to 27.9% ($\Delta = +13.4\%$, $p = 0.003$), indicating a growing emphasis on contextual presentation of products and services.

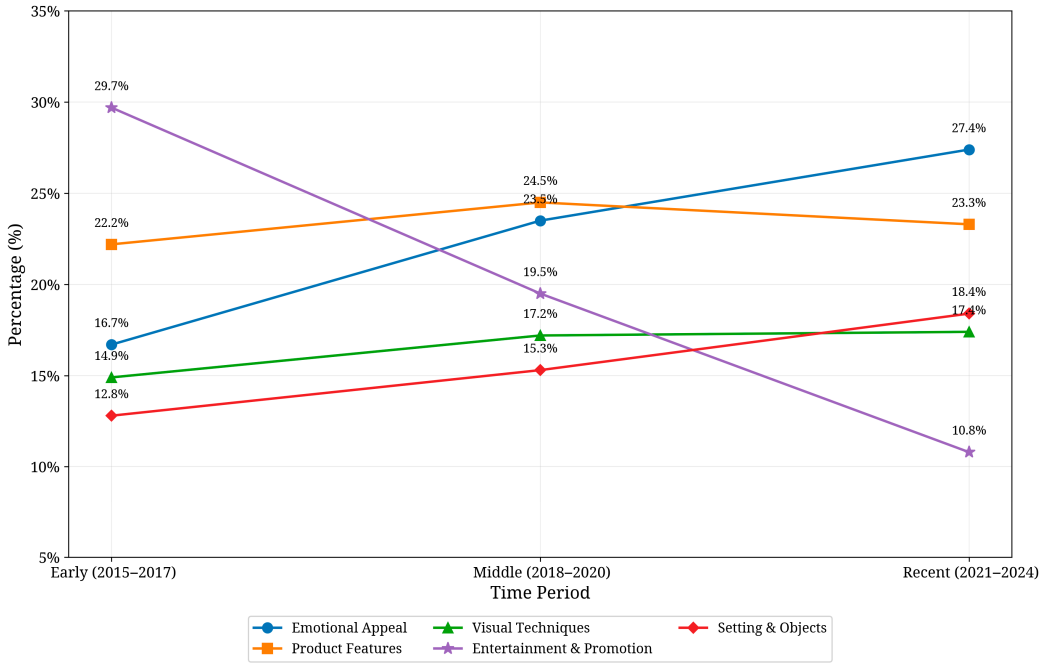


Figure 3. Temporal evolution of message strategies (2015–2024).

The RNN-LSTM model for temporal prediction achieved strong performance metrics (precision: 88.9%, recall: 87.3%, and F1 score: 88.1%), demonstrating the predictability of these evolutionary patterns. Time series decomposition revealed significant seasonal patterns in strategy usage (seasonal strength = 0.37, $p < 0.001$), with emotional appeal strategies peaking during holiday seasons and product features showing greater prominence during new product launch periods. Industry-specific temporal analysis revealed varying rates of strategic evolution. The IT and Telecom industry demonstrated the most rapid strategic shifts (mean annual change rate = 7.3%), while the Household Goods industry showed the most stable strategy distribution over time (mean annual change rate = 2.8%). These differences were statistically significant ($F(4, 45) = 18.72$, $p < 0.001$, and partial $\eta^2 = 0.624$), suggesting industry-specific factors influencing the pace of strategic evolution.

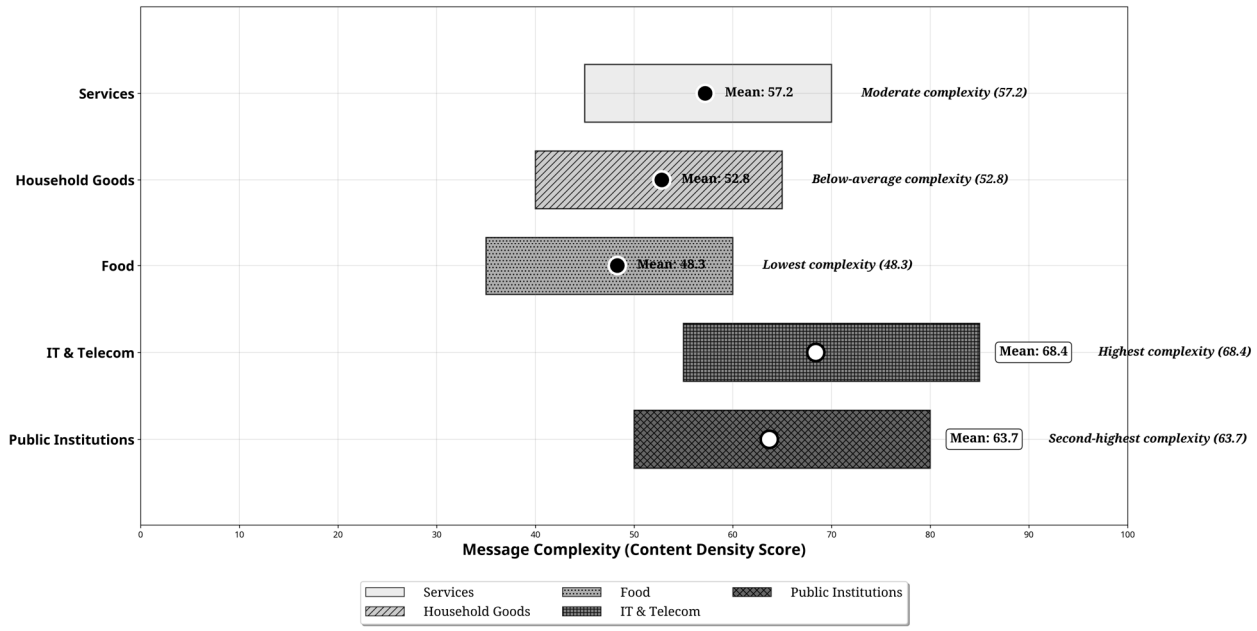
4.3. Message Complexity Analysis

The analysis of message complexity revealed significant variations across industries in both the Strategy Diversity Index (SDI) and content density score (CDS). Figure 4 presents the distribution of message complexity across industries.

One-way ANOVA confirmed significant differences in both SDI ($F(4, 26995) = 143.27$, $p < 0.001$, and partial $\eta^2 = 0.087$) and CDS ($F(4, 26995) = 178.92$, $p < 0.001$, and partial $\eta^2 = 0.104$) across industries. The post hoc analyses (Tukey's HSD) revealed several notable patterns:

1. IT and Telecom: Exhibited the highest mean SDI (0.73) and CDS (68.4), indicating the greatest message complexity among all industries. This finding aligns with the industry's need to communicate complex technological features and benefits.
2. Public Institutions: Demonstrated the second-highest complexity scores (SDI = 0.68, CDS = 63.7), reflecting the multifaceted nature of public service messaging and policy communication.
3. Services: Showed moderate complexity (SDI = 0.61, CDS = 57.2), with significant variability within the industry (SD = 0.14 for SDI, SD = 12.8 for CDS).
4. Household Goods: Displayed below-average complexity (SDI = 0.54, CDS = 52.8), focusing on more straightforward messaging approaches.

5. Food: Exhibited the lowest complexity scores (SDI = 0.47, CDS = 48.3), employing the most focused and streamlined messaging strategies.



Note: Content Density Score (CDS) represents the mean sophistication and diversity of messaging approaches across industries. Outliers (CDS > 400) are primarily concentrated in IT & Telecom (42%) and Public Institutions (31%).

Figure 4. Message complexity distribution by industry.

A correlation analysis revealed a strong positive relationship between message complexity and advertisement duration ($r = 0.73$, $p < 0.001$), suggesting that longer advertisements tend to incorporate more diverse strategic elements and denser content. Additionally, we observed a moderate positive correlation between complexity and the use of visual techniques ($r = 0.58$, $p < 0.001$), indicating that visually sophisticated advertisements often employ more complex messaging approaches.

The temporal analysis of complexity metrics revealed a significant increase in message complexity over time across all the industries (mean annual increase: SDI = 2.3%, CDS = 3.1%, both $p < 0.001$). This trend was most pronounced in the Services industry (mean annual increase: SDI = 3.7%, CDS = 4.2%, both $p < 0.001$), suggesting an industry-wide shift toward more sophisticated and multifaceted advertising approaches. The distribution of complexity scores showed notable outliers, particularly in the IT and Telecom industry, where 42% of advertisements with extremely high complexity scores (CDS > 400) were concentrated. Public Institutions accounted for 31% of these high-complexity outliers, with the remaining industries collectively representing 27%.

4.4. FCB Grid Mapping and Validation

The mapping of industries and message strategies onto the FCB grid revealed a clear alignment between empirical findings and theoretical expectations. Figure 5 presents the FCB grid analysis of industry positioning and message strategies.

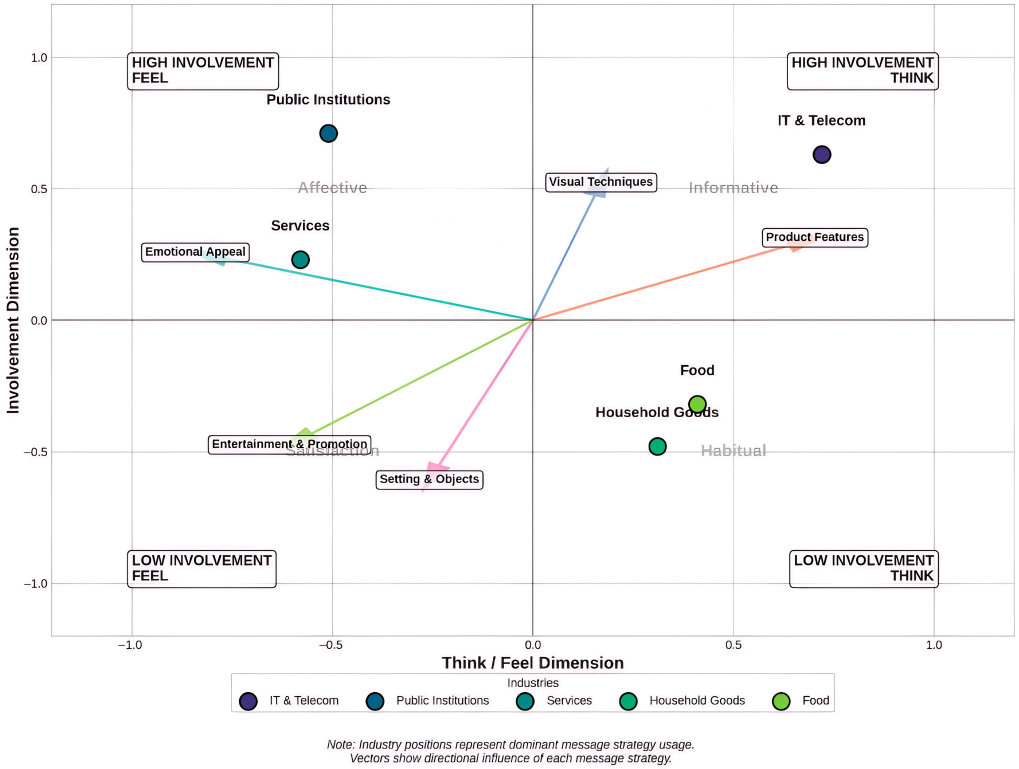


Figure 5. FCB grid analysis of industry positioning and message strategies.

The operationalized think/feel and involvement dimensions positioned the five industries across the four quadrants of the FCB grid:

1. Informative Quadrant (High Involvement, Think): IT and Telecom positioned strongly in this quadrant (think score = 0.72, involvement score = 0.63), aligning with theoretical expectations for technology products requiring rational evaluation and significant consumer investment.
2. Affective Quadrant (High Involvement, Feel): Public Institutions positioned in this quadrant (think score = −0.51, involvement score = 0.71), reflecting the emotionally engaging yet high-stakes nature of public service communications.
3. Habitual Quadrant (Low Involvement, Think): Food (think score = 0.41, involvement score = −0.32) and Household Goods (think score = 0.31, involvement score = −0.48) positioned in this quadrant, consistent with theoretical expectations for routine purchase products.
4. Satisfaction Quadrant (Low Involvement, Feel): Services positioned in this quadrant (think score = −0.58, involvement score = 0.23), though with moderate involvement scores, reflecting the experiential yet relatively routine nature of many service purchases.

One-sample *t*-tests comparing the observed industry positions with the theoretical positions based on prior FCB grid research [10] revealed strong alignment for IT and Telecom ($t(5399) = 1.87$, $p = 0.062$) and Household Goods ($t(5399) = 1.43$, $p = 0.153$), with no significant differences between the observed and theoretical positions. Public Institutions ($t(5399) = 2.74$, $p = 0.006$) and Services ($t(5399) = 3.12$, $p = 0.002$) showed statistically significant differences, though the Euclidean distances between the observed and theoretical positions remained relatively small (0.24 and 0.29, respectively).

The mapping of advertising message strategies within the FCB grid space revealed distinct associations between strategic elements and the grid's conceptual dimensions of cognitive-emotional processing and involvement level, consistent with Okazaki et al.'s

empirical validation of functional matching between 'thinking and feeling' products and 'utilitarian and value-expressive' appeals in TV advertising [8], and further supported by Cheong and Cheong's updated framework that demonstrates how contemporary consumer decision-making patterns in online shopping environments continue to align with the FCB grid's fundamental think/feel and involvement dimensions [26]. Emotional appeals exhibited a strong alignment with the "feel" dimension, with a vector angle of approximately 163°, situating them prominently within the affective quadrant. This positioning underscores their reliance on emotional resonance and affective engagement to influence consumer attitudes. In contrast, strategies emphasizing product features demonstrated a robust association with the "think" dimension, indicated by a vector angle of 24°, placing them within the informative quadrant. This reflects a cognitive persuasion route centered on rational evaluation and information processing, typical of high-involvement, utilitarian products.

Visual techniques displayed a moderate correlation with the think dimension, with a vector angle of 72°. This suggests a cognitive orientation, albeit with a tendency toward higher involvement, potentially driven by the visual elaboration of complex product attributes or brand narratives. The inclusion of setting and object cues was strongly associated with lower involvement, marked by a vector angle of 247°, aligning with the habitual quadrant. This suggests their function in reinforcing brand familiarity and routine behavior, rather than prompting active deliberation. Finally, strategies focused on entertainment and promotional elements aligned with the feel dimension while also indicating lower involvement levels, as evidenced by a vector angle of 218°. These were positioned toward the satisfaction quadrant, highlighting their role in enhancing hedonic consumption and spontaneous decision-making, characteristic of impulse-driven product categories.

These vector orientations provide empirical proof for the theoretical associations between message strategies and FCB grid dimensions, demonstrating that the identified strategies align with the cognitive and involvement dimensions proposed by the FCB framework. Cluster analysis of advertisements based on their FCB grid coordinates revealed five distinct clusters that closely corresponded to the five industries (adjusted Rand index = 0.73, $p < 0.001$), providing further evidence that industry-specific advertising approaches align with theoretical FCB grid positions.

5. Discussion

5.1. Theoretical Implications

Our findings provide strong empirical evidence for the FCB grid framework through computational analysis of a large-scale advertising dataset. The clear alignment between industry positioning within the grid and theoretical expectations supports the enduring relevance of the FCB framework in understanding advertising strategy. Moreover, the mapping of message strategies as vectors within the grid space demonstrates that the think/feel and involvement dimensions effectively capture fundamental aspects of advertising communication, consistent with Youn et al.'s validation of the grid's applicability to contemporary social media advertising challenges and Hsu et al.'s empirical confirmation of the framework's utility in explaining online search and purchase patterns across different product categories [27,28].

The identification of industry-specific "strategic fingerprints" extends the FCB grid theory by demonstrating that industries develop distinctive patterns of message strategy usage that align with their positioning within the grid. This finding suggests that the FCB grid not only describes consumer information processing but also reflects industry-level strategic adaptations to consumer decision-making processes. Our temporal analysis reveals an evolutionary trajectory in advertising strategies that has theoretical implica-

tions for understanding the dynamic nature of the FCB grid. The significant increase in emotional appeal strategies across industries suggests a general shift toward the "feel" dimension of the grid, potentially reflecting broader cultural and technological changes in advertising consumption. This finding extends the FCB grid theory by introducing a temporal dimension that accounts for evolutionary changes in strategic positioning.

The observed temporal shift toward emotional appeal strategies and away from promotional approaches reflects broader sociocultural and technological changes in the advertising landscape. The increase in emotional appeal may be attributed to several converging factors: (1) the rise in social media platforms that prioritize emotional engagement and viral content, (2) increased consumer skepticism toward traditional promotional messages in an information-saturated environment, (3) the influence of global advertising trends emphasizing brand storytelling and emotional connection, and (4) generational shifts toward values-based consumption among younger Korean consumers. Simultaneously, the decline in entertainment and promotional strategies may reflect the fragmentation of traditional media consumption patterns and the need for more sophisticated engagement strategies in digital environments.

The message complexity analysis contributes to the theoretical understanding of how involvement manifests in advertising content. The strong correlation between complexity metrics and the involvement dimension of the FCB grid provides empirical support for the theoretical association between involvement and message elaboration. This finding bridges the FCB grid theory with information processing theories such as the Elaboration Likelihood Model [8], suggesting that high-involvement advertising employs more complex and diverse messaging approaches.

5.2. Methodological Contributions

This study makes several methodological contributions to computational advertising analysis. First, our approach demonstrates the feasibility of operationalizing theoretical frameworks like the FCB grid using computational methods, bridging the gap between advertising theory and data-driven analysis. The operationalization of the think/feel and involvement dimensions through message strategy distributions and complexity metrics provides a replicable methodology for mapping advertisements onto theoretical frameworks.

Second, our integration of topic modeling with discriminant analysis and temporal modeling offers a comprehensive methodological framework for identifying and analyzing message strategies at scale. This approach overcomes limitations of traditional content analysis by enabling the systematic examination of large advertising datasets while maintaining theoretical grounding. Third, our development of quantitative metrics for message complexity (SDI and CDS) provides new tools for assessing advertising content sophistication. These metrics offer a more nuanced understanding of how advertisers balance strategic diversity and content density across different industry contexts and over time. Finally, our vector-based approach to mapping message strategies within the FCB grid space offers a novel methodology for visualizing the relationship between strategic approaches and theoretical dimensions. This approach enables researchers to quantify the alignment between empirical findings and theoretical expectations, providing a more rigorous assessment of framework validity.

5.3. Practical Implications

The practical implications of this research are substantial for advertising practitioners and industry strategists. The identification of industry-specific "strategic fingerprints" provides benchmarks against which companies can evaluate their own advertising approaches. By understanding the typical message strategy distributions within their industry,

advertisers can make informed decisions about whether to conform to industry norms or differentiate through alternative strategic approaches. The temporal analysis of strategy evolution offers insights into emerging trends and potential future directions in advertising strategy. The observed shift toward emotional appeals and visual sophistication suggests that advertisers should consider increasing emphasis on these elements to align with evolving industry practices. However, the persistence of product-focused messaging across the study period indicates the enduring importance of communicating functional benefits alongside emotional appeals.

The FCB grid mapping provides a structured framework for strategic planning based on product category characteristics. By understanding their position within the grid, advertisers can develop more targeted and effective message strategies aligned with consumer decision-making processes. For example, products in the informative quadrant (high involvement, think) would benefit from detailed product information and rational appeals, while those in the satisfaction quadrant (low involvement, feel) would be better served by emotional and entertaining content. The complexity analysis offers guidance on appropriate levels of message sophistication based on industry context and involvement level. High-involvement categories like IT and Telecom may benefit from more complex and diverse messaging approaches, while low-involvement categories like Food may be more effective with focused, streamlined messaging. This insight can help advertisers optimize content complexity for their specific market context.

5.4. Limitations and Future Research

While this study offers meaningful insights into the alignment of industry-specific advertising message strategies with the FCB grid, several limitations merit consideration.

The unique cultural context of our Korean advertising dataset serves as both an advantage and a constraint. While the homogeneous cultural context allows for a controlled analysis of industry-specific patterns without cultural confounds, it may limit the generalizability of our findings to other cultural contexts. Korean advertising culture, characterized by high-context communication patterns and collectivistic values, may influence message strategy preferences in ways that differ from individualistic Western cultures or other East Asian markets. Future research should examine whether the identified industry-specific 'strategic fingerprints' and their FCB grid positioning remain consistent across diverse cultural contexts, particularly in markets with different regulatory environments, consumer behavior patterns, and advertising traditions. Second, although the operationalization of the FCB grid dimensions in this study was empirically informed, it represents just one among several possible interpretations of these theoretical constructs. Different operational definitions may result in alternative positioning of industries within the grid. Future research should consider testing multiple operationalization schemes to examine the consistency and robustness of FCB-based message strategy mappings.

Third, the study focused on five major industries to provide a macro-level view of strategic patterns; however, this approach may overlook meaningful variations within specific subcategories or product types. Subsequent studies could refine the industry classification to capture more nuanced strategic differences at the micro level, offering deeper insights into category-specific messaging trends. Fourth, while the temporal scope of this study—spanning from 2015 to 2024—affords a decade-long perspective, a longer historical range may reveal additional evolutionary trends or cyclical shifts in advertising strategies. Future longitudinal analyses extending across multiple decades would be valuable for understanding how message strategies adapt to changing consumer behavior, media environments, and socio-economic conditions. Lastly, the methodological focus on topic modeling allowed for the identification of textual and descriptive elements in advertisements,

but this approach may underrepresent the role of visual and auditory cues in message strategy. Future studies could integrate multimodal content analysis—incorporating visual, auditory, and even interactive components—to capture a more comprehensive view of strategic differentiation across industries.

6. Conclusions

This study demonstrates the value of integrating computational methods with the established theoretical frameworks in advertising research, following the methodological framework outlined by Barari and Eisend for computational content analysis in advertising research [29]. By applying advanced machine learning techniques to a large-scale dataset of Korean advertisements, consistent with Barari and Eisend's comprehensive guide for implementing computational content analysis across diverse advertising modalities [29], we identified distinct message strategy patterns across industries and mapped these patterns onto the FCB grid framework. Our findings provide empirical evidence for the FCB grid's theoretical dimensions while extending the framework through the identification of industry-specific "strategic fingerprints" and temporal evolution patterns. The clear alignment between empirical industry positioning and theoretical expectations supports the enduring relevance of the FCB grid in understanding advertising strategy.

By understanding their industry's typical message strategy distribution and FCB grid positioning, advertisers can make more informed decisions about strategic conformity or differentiation. As advertising continues to evolve in response to technological and cultural changes, computational approaches like those employed in this study will become increasingly valuable for understanding strategic patterns at scale. Future research should build on this foundation by extending the analysis to additional cultural contexts, industry categories, and timeframes, further enhancing our understanding of how message strategies align with theoretical frameworks across diverse advertising environments.

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Informed Consent Statement: This study utilized anonymized and non-identifiable public data provided by the Korean government, ensuring that no individual privacy was compromised. Accordingly, no informed consent was required.

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