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The Impact of Visual Attributes on User Engagement in B2B Social Media

Michal PLECHÁČ*, Matěj JUHÁSZ and Pavel BACHMANN

University of Hradec Králové, Hradec Králové, Czech Republic; michal.plechac@uhk.cz; matej.juhasz@uhk.cz; pavel.bachmann@uhk.cz

* Corresponding author: michal.plechac@uhk.cz

Abstract: This study examines the impact of specific visual attributes on user engagement within the professional social network LinkedIn, focusing on the B2B automotive sector. While B2B marketing increasingly relies on content distribution, empirical evidence regarding granular visual execution remains fragmented. The research analyzes a dataset of 319 posts from major Tier-1 automotive suppliers, collected between June and November 2025. Using a quantitative observational design, four visual dimensions were coded: photography type, presence of people, text overlay, and branding intensity. Non-parametric statistical analysis (Kruskal-Wallis and Mann-Whitney U tests) revealed that "clean" photography and images without text overlays significantly outperform hybrid visual formats containing graphical elements or headlines. Contrary to trends on other social platforms, the presence of human faces and high brand prominence did not yield a statistically significant increase in reactions. The findings suggest that professional audiences exhibit "banner blindness" toward ad-like visual signals. Consequently, B2B marketers are advised to prioritize visual authenticity and minimize text-heavy graphics to enhance user engagement.

Keywords: LinkedIn; B2B marketing; user engagement; visual attributes; automotive industry

JEL Classification: M31; M37; L62

1. Introduction and Literature Review

In recent years, the professional social network LinkedIn has established itself as a key channel for B2B communication, employer branding, and building trust in industrial sectors. Unlike entertainment-oriented platforms, the dominant context here is professional identity, reputation, and business relationships. Consequently, the audience evaluates content through the lens of competence, relevance, and credibility. Within B2B marketing, there has been a long-term shift from "push" advertising to a "pull" approach—creating and distributing content that is practically useful to the audience, thereby fostering relationships and trust (Holliman & Rowley, 2014; Järvinen & Taiminen, 2016).

In this logic, LinkedIn becomes an environment where individual posts compete for limited user attention in a rapidly changing feed. The success of content shifts from merely conveying the correct message to the ability to capture attention and provoke interaction

(reactions, comments, shares). Research in the B2B context indicates that engagement is not just a superficial metric; it correlates with relationship building and perceived content value. For instance, Sundström et al. (2021) suggest that action-oriented messages may generate higher engagement than purely product-oriented or abstract value framing. However, the visual component of posts acts as the primary filter. Users typically process the visual signal first—photography, graphics, composition—before paying attention to the text.

A critical challenge in this domain is the phenomenon of "banner blindness." Benway (1998) empirically demonstrated that users often overlook salient, colorful elements if they perceive them as "ads" rather than useful information. This mechanism is highly relevant to social feeds: if a visual carries "ad-like" signals (e.g., heavy text overlay, artificial composition), it may be subconsciously filtered out as less trustworthy. Conversely, while studies on platforms like Instagram suggest that human faces increase engagement (Bakhshi et al., 2014), the effect in a professional B2B context remains ambiguous.

Despite the growing body of research on B2B social media strategies, empirical evidence specifically focusing on the granularity of visual attributes—such as the type of photography, presence of text in images, or branding intensity—remains fragmented. Existing studies often address general content strategies rather than specific visual execution (Sundström et al., 2021) or focus on the source of the message (Balaji et al., 2023).

The aim of this paper is to identify which specific visual elements of LinkedIn posts are associated with statistically significant differences in user engagement, specifically measured by the number of Reactions. The study analyzes a dataset of 319 posts from the automotive industry, focusing on four visual dimensions: Photography Code (visual type), People Code (presence of people), Text Code (text in image), and Brand Code (branding visibility). The research addresses the following questions: Does the level of reactions differ significantly based on the type of visual used, the presence of people, the inclusion of text in the image, or the intensity of branding? By answering these questions using robust non-parametric statistical methods, this study provides practical implications for optimizing B2B visual communication to avoid "ad-like" signals and maximize authentic engagement.

2. Methodology

The research employs a quantitative observational design based on the analysis of published posts on the professional network LinkedIn. The unit of analysis is a single LinkedIn post. To ensure compliance with LinkedIn's Terms of Service regarding automated data scraping, data collection was conducted manually. The observational period spans six months, from June 2025 to November 2025. The dataset consists of $N = 319$ posts collected from the seven largest Tier-1 automotive suppliers in the European Union. These companies were selected based on revenue rankings for the year 2024, as reported by the automotive consulting firm Berrylls (Top 100 Archive, 2026). For each post, engagement metrics (Reactions, Comments, Shares) were collected, along with a set of manually coded visual attributes. The primary dependent variable for this study is the number of Reactions, as it represents the most immediate and low-cost form of user feedback, suitable for capturing the "first impression" effect of the visual content.

2.1. Operationalization of Variables

The independent variables represent visual attributes categorized into four dimensions, coded on a scale of 0–2:

- Photography Code: 0 = clean photography; 1 = photo with graphics/overlay; 2 = artificial graphics/collage.
- People Code: 0 = no people; 1 = people in background/partial; 2 = specific recognizable people.
- Text in Image Code: 0 = clean image (no text); 1 = headline only; 2 = message/detailed info.
- Brand Code: 0 = no branding; 1 = weak branding; 2 = strong branding.

2.2. Statistical Analysis and Hypotheses Testing

The statistical analysis was performed using Python (libraries pandas, SciPy, matplotlib). First, the assumption of normality for the dependent variable (Reactions) was tested using the Shapiro-Wilk test (Shapiro & Wilk, 1965). The test results indicated a significant deviation from normality ($W = 0.694, p < 0.001$), confirming the "heavy-tail" distribution typical for social media engagement metrics. Consequently, non-parametric methods were selected for hypothesis testing.

To answer the research questions regarding the differences in reactions across visual categories, the Kruskal-Wallis H test was employed as a non-parametric alternative to one-way ANOVA (Kruskal & Wallis, 1952). The effect size for the omnibus test was estimated using epsilon-squared (ϵ^2).

Where the omnibus test indicated statistically significant differences, post-hoc pairwise comparisons were conducted using the Mann-Whitney U test (Mann & Whitney, 1947). To control for the family-wise error rate in multiple comparisons, the Bonferroni correction was applied (Bonferroni, 1936). The effect size for pairwise differences was reported using the rank-biserial correlation coefficient $r = Z/\sqrt{N}$. Finally, Spearman's rank correlation coefficient (ρ) was used to explore relationships between visual variables and among different engagement metrics (Spearman, 1904). The significance level was set at $\alpha = 0.05$.

3. Results

This section presents the results of the inferential analysis examining the differences in user engagement (Reactions) across four visual dimensions: Photography, People, Text in Image, and Brand. Due to the non-normal distribution of the dependent variable, non-parametric tests were applied.

3.1. Visual Attributes Based on Omnibus Testing

First, the Kruskal-Wallis H test was conducted to determine if there are statistically significant differences in the median number of reactions between categories for each visual attribute. The results are summarized in Table 1.

Table 1. Results of Kruskal-Wallis H test for reactions (df = 2)

Factor	H-statistic	p-value	ϵ2 (Effect Size)	Conclusion
Photography Code	21.588	< .001	0.062	Significant
People Code	1.602	.449	~0.000	Not significant
Text in Image Code	17.042	< .001	0.048	Significant
Brand Code	3.880	.144	0.006	Not significant

Note: Significance level α = 0.05.

The analysis revealed statistically significant differences for Photography Code (p < .001) and Text in Image Code (p < .001). In contrast, neither the presence of people nor the intensity of branding showed a significant effect on the number of reactions in this dataset.

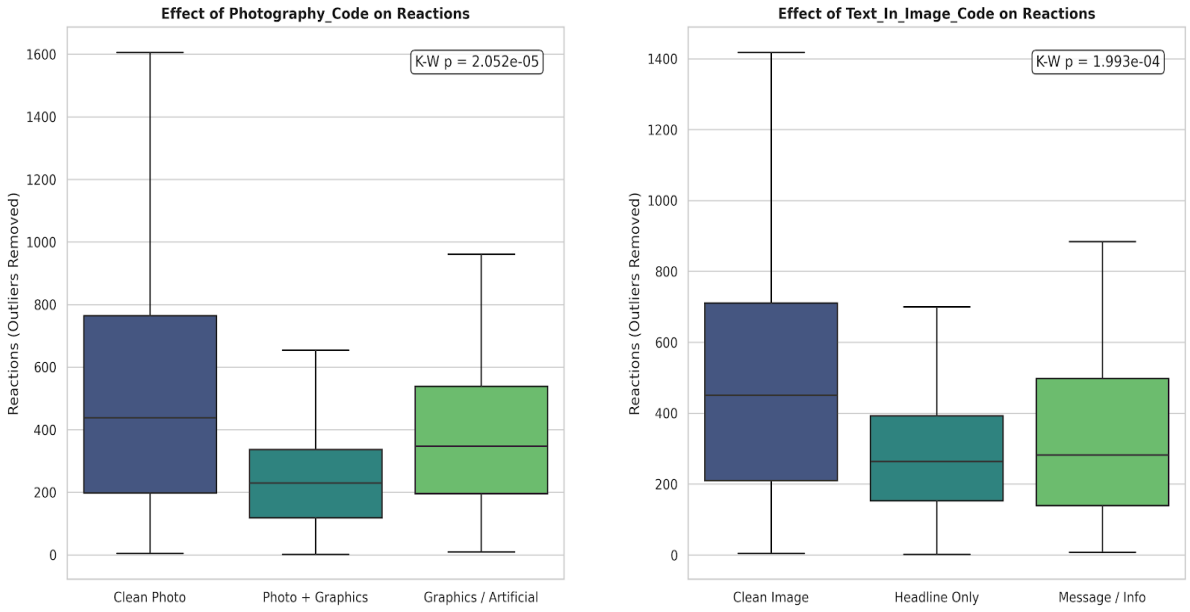

Figure 1. Boxplots showing the distribution of Reactions across categories of Photography Code (left) and Text in Image Code (right).

3.2. Post-hoc Pairwise Comparisons

For the factors that showed significant results in the omnibus test, post-hoc pairwise comparisons were performed using the Mann-Whitney U test with Bonferroni correction for multiple comparisons (p_{adj} < .017).

For Photography Code, the "Clean Photo" category (Median = 438) significantly outperformed the "Photo + Graphics" category (Median = 229.5), with a medium effect size (r = 0.289). The difference between "Clean Photo" and "Graphics/Artificial" was not statistically significant.

For Text in Image Code, posts with a "Clean Image" (no text overlay) achieved significantly higher engagement (Median = 451) compared to both "Headline Only" (Median = 264) and "Message/Info" (Median = 282). No significant difference was found between the two text-heavy categories.

Table 2. Selected Post-hoc Mann-Whitney U test results (Bonferroni adjusted)

Comparison (Group A vs. Group B)	Median A	Median B	padj	Comparison (Group A vs. Group B)
Photography: Clean Photo vs. Photo + Graphics	438	229.5	< .001	0.289
Photography: Clean Photo vs. Graphics/Artificial	438	347.5	.755	0.072
Text: Clean Image vs. Headline Only	451	264	.002	0.213
Text: Clean Image vs. Message/Info	451	282	.006	0.192

3.3. Relationships Among Variables

Spearman's rank correlation analysis was used to explore the relationships between visual attributes and engagement metrics. A correlation heatmap is presented in Figure 2.

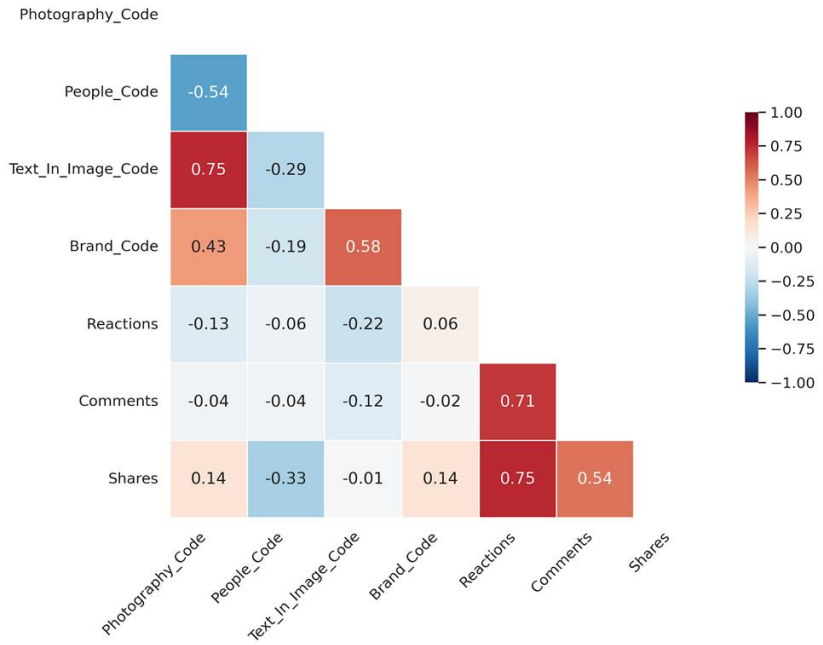

Figure 2. Spearman correlation matrix of visual codes and engagement metrics (Reactions, Comments, Shares).

The analysis identified significant correlations between visual attributes, suggesting that they often appear in clusters. For instance, Photography Code is strongly correlated with Text in Image Code ($\rho = 0.748, p < .001$), indicating that artificial or graphic-heavy visuals are more likely to contain text. Regarding engagement metrics, Reactions are strongly positively correlated with Comments ($\rho = 0.710$) and Shares ($\rho = 0.751$). Interestingly, while the People Code did not significantly affect Reactions, it showed a negative correlation with Shares ($\rho = -0.332, p < .001$), suggesting that posts featuring specific people might be shared less frequently.

4. Discussion

The primary objective of this study was to determine how specific visual attributes influence user engagement on LinkedIn in a B2B context. The results indicate that

"cleanliness" and the absence of "ad-like" features are significant drivers of reactions, while the presence of people or branding intensity plays a less decisive role than often assumed.

4.1. Authenticity Over Artificiality and Banner Blindness

The analysis revealed a significant preference for "Clean Photos" over "Photo + Graphics" hybrid formats. This finding aligns with the theory of source credibility in B2B marketing; visual forms that appear organic are perceived as more authentic, whereas heavy graphical overlays may signal "marketing fabrication" (Balaji et al., 2023). Similarly, the negative impact of text overlays on reactions supports the "banner blindness" phenomenon described by Benway (1998). Users in a professional feed likely filter out content that visually resembles advertisements or flyers (high text density, artificial composition) to focus on information they perceive as relevant (Cho & Cheon, 2004). The "binary penalization" observed—where *any* text overlay significantly reduced performance compared to clean images—suggests that the mere presence of text acts as a heuristic cue for ad avoidance.

4.2. The Ambiguous Role of Human Elements and Branding

Contrary to findings on social platforms like Instagram, where faces typically drive higher engagement (Bakhshi et al., 2014), this study found no significant difference in reactions based on the People Code. This discrepancy highlights the specific nature of the professional B2B context, where the relevance of the message may outweigh the emotional appeal of a human face. Furthermore, a negative correlation was observed between the presence of specific people and the number of Shares ($\rho = -0.33$), suggesting that while "human" posts are well-received, they are viewed as internal or personal content that users are less inclined to share with their own professional network. The lack of significant impact from the Brand Code implies that branding acts as a hygiene factor rather than a driver of engagement in the automotive B2B sector. Moreover, high brand prominence can sometimes trigger ad avoidance mechanisms if the content is perceived as purely promotional (Xiao et al., 2024).

4.3. Limitations

The study has several limitations.

First, the dataset is restricted to the automotive Tier-1 industry ($N = 319$) and spans a six-month observational period (June–November 2025). This limited timeframe may exclude seasonal trends or specific industry events typical of the full annual cycle, potentially affecting the temporal generalizability of the results.

Second, the analysis relies on absolute interaction counts (Reactions) without normalizing for Reach or Impressions, which were unavailable. Similarly, the study does not control for the varying follower base sizes of the included companies, which naturally biases absolute engagement numbers towards larger accounts. Consequently, it is impossible to strictly separate the effect of "better creative" from "algorithmic distribution" or brand popularity.

Furthermore, the manual coding of visual attributes was performed by a single researcher. While a standardized codebook was utilized, the absence of multiple coders prevents the assessment of Intercoder Reliability (ICR). Future research should incorporate multiple independent coders to validate these visual constructs and mitigate potential subjective bias.

Finally, the univariate non-parametric approach does not account for the interaction effects between variables, nor does it consider the influence of textual captions (copywriting quality, length, hashtags), which act as a significant confounding variable in driving user engagement.

5. Conclusions

This paper empirically examined the impact of visual attributes on LinkedIn user engagement. The findings challenge the common practice of using heavily designed, text-rich visuals in B2B communication. The statistical analysis confirmed that "Clean Photography" and "Clean Images" (without text overlays) significantly outperform hybrid formats and visuals containing headlines or detailed information. Conversely, the presence of people and strong branding did not yield a statistically significant increase in Reactions.

5.1. Managerial Implications

Based on these results, B2B marketers should:

- Minimize text in images: Move headlines and detailed information to the post caption to avoid triggering banner blindness.
- Prioritize visual authenticity: Avoid "hybrid" formats (photos with graphical overlays) that resemble flyers. Use high-quality, authentic photography instead.
- Use human elements strategically: Recognize that while photos of people may build community, they are less likely to be shared virally compared to content focused on products or industry insights.

Future research should incorporate exposure metrics (Reach/Impressions) to calculate engagement rates and employ multivariate regression models to isolate the specific effects of overlapping visual attributes.

Conflict of interest: none

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