

Brand-Related Posts on Social Media: The Effect of Product Type on Consumers' UGC

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Abstract. *This study examines the role of user-generated content (UGC) in shaping brand engagement across two social media platforms, Instagram and X, with a focus on how the nature of the product (utilitarian vs. hedonic) interacts with platform-specific characteristics. Using Latent Dirichlet Allocation (LDA) for text analysis, the research explores UGC terminology, sentiment, and platform-specific differences to identify key patterns in consumer behavior. Findings indicate that utilitarian products generate more functional UGC, particularly on X, while hedonic products elicit more symbolic and self-expressive content, predominantly on Instagram. Additionally, sentiment analysis reveals a general positivity bias in UGC, with hedonic products receiving more positive sentiment on Instagram than on X. We provide theoretical contributions by linking product type, platform features, and consumer sentiment while offering actionable insights for marketers on tailoring communication strategies to specific platforms and product categories. These results highlight the value of platform segmentation, sentiment monitoring, and targeted campaigns to optimize consumer engagement in the dynamic context of contemporary social media.*

Keywords: UGC, social media, platform differences, utilitarian, hedonic.

JEL Codes: M15, M31, M37

1. Introduction

Social media platforms such as Instagram, X (formerly Twitter), and Facebook allow users to interact, express, share, and create brand-related content. For example, consumers share Absolut Vodka videos on YouTube, discuss Monster energy drinks on X, and post Nike sneaker photos on Instagram. This type of engagement, known as user-generated content (UGC), significantly shapes brand perceptions (Christodoulides et al., 2012; Wei, 2024).

Numerous studies demonstrate UGC's impact on purchase intentions (Muda & Hamzah, 2021) and sales performance (Sajedikhah et al., 2023). However, poor implementation indicates that UGC does not always benefit brands (Vinales & Thomas, 2020), highlighting the need for better understanding of how to encourage deliberate and effective consumer engagement within digital spaces.

A major challenge in utilizing UGC lies in its textual and graphic nature, as well as the significant amount of UGC available. For instance, as of February 2025, X and Instagram had a combined 2586 million monthly active users worldwide (We Are Social, & DataReportal, & Meltwater, 2025).

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Although research on extracting insights from social media text has increased in the last years, only a few studies examined brand related posts in depth. For example, Liu et al. (2017) found that brand discussions topics vary by industry and type of product/service, and Keller (1993) showed that purchase decisions are not influenced only by functional, but also by experiential and symbolic attributes. These papers offer a solid foundation for UGC research, but it is still unclear how UGC differs across product categories, especially functional (tools etc.) versus symbolic ones (luxury, etc.).

Additionally, few studies compare UGC across different sites, whereas some analyze UGC on individual platforms. Although Smith et al. (2012) observed notable variations in user-generated content on Facebook, X, and YouTube, their analysis was restricted to two clothing brands targeted at women, which limited the scope of their findings. Cross-platform comparisons could help marketers co-create brand meaning across different digital environments.

This research expands upon previous investigations by examining user-generated content (UGC) in the context of product classification (utilitarian versus symbolic) and platform variations (Instagram versus X), while also taking into account product tangibility. Research indicates that utilitarian items may face challenges on social media due to their restricted emotional appeal (Krishen et al., 2019) and the fact that these platforms are predominantly utilized for entertainment (Helmi et al., 2023). However, baby diapers is an example of a utilitarian product that may do well on social media (Millward Brown, 2011), where Pampers was the second most popular brand. These varied results mean that we need to look more closely into whether and how utilitarian brands do well on social media.

This research examines two principal inquiries: (1) What are the differences in UGC facets (like subjects and sentiment) for utilitarian and hedonic products on each platform? (2) How do these UGC aspects differ between Instagram and X? We want to help marketers come up with tactics for each platform and product that will get people more involved.

The paper continues with a review of the literature, then moves to hypotheses, methodology, results, discussion, and implications for future research and marketing practice.

2. Background Literature and Hypotheses Development

2.1. Product Type

There has been an increasing interest in examining the textual content of brand-related user-generated content (UGC) across diverse products and businesses. Xue et al. (2020) utilized Latent Dirichlet Allocation (LDA) (Blei et al., 2003) to analyze public discussions during the COVID-19 epidemic, uncovering significant topics and sentiments that illustrated individual coping mechanisms and communication patterns. Hammad et al. (2022) employed the same methodology to investigate social media discussions around Mandalika, a special economic zone in Indonesia, providing insights into popular perceptions and attitudes. Nonetheless, this research did not investigate the impact of product type on social media discussions. Understanding how consumers approach utilitarian versus hedonic products on different platforms is essential for marketers.

Research in advertising and consumer behavior has explored a variety of ways to classify products. As noted, this research is particularly interested in products that are either hedonic or utilitarian in nature (Hirschman & Holbrook, 1982). Hedonic products enable people to express their ideal or actual self-image (Khalil, 2000) and are consumed for sensory pleasure and gratification (Holbrook, 1986; Woods, 1960). They are prized for their taste, aesthetics, sensory experience, and symbolic meaning (Holbrook & Moore, 1981), and they arouse emotions (Mano & Oliver, 1993). Symbolic benefits satisfy demands for self-esteem, social acceptance, or personal expression and are frequently associated with non-functional qualities. On the other hand, cognitively oriented advantages are offered by practical items like lawn mowers, washing machines, and

hair dryers (Hirschman & Holbrook, 1982; Strahilevitz & Myers, 1998; Woods, 1960). Customers typically rely on logical assessment and concentrate on the functional features of these products (Kempf, 1999).

H1: UGC about hedonic products will have more symbolic than functional terms (H1b), while UGC about utilitarian products will have more functional than symbolic terms (H1a).

2.2. Social Media Sites

Whereas differences in brand-related topics are expected across product types (utilitarian versus hedonic), we also anticipate differences across social media platforms. Smith et al. (2012) found that YouTube, X, and Facebook all had notable variations in brand-related user-generated content. However, since their analysis was restricted to two clothing brands that primarily catered to women, it is challenging to generalize their findings. Additionally, the study used manual coding instead of text mining.

This study is focusing on two of the main social media platforms: X and Instagram, due to their relatively similar US market penetration. StatCounter (2025) reports that 11.7% of all social media site visits account for X, and 10% for Instagram.

X is a popular microblogging site that lets users post, respond to, and share brief content limited to 280 characters for free accounts (X Developer Platform, 2023). The main topics found on X pertain to sharing of information, news, opinions, grievances, and daily updates. As of February 2025, X had 586 million monthly active users since its 2006 launch (We Are Social, & DataReportal, & Meltwater, 2025). With 67% of users saying they buy from brands they follow (Malhotra et al., 2011), the platform gives brands access to devoted customers.

Instagram, a mobile photo and video sharing app that was introduced in 2010, has reached 2 billion users by February 2025 (We Are Social, & DataReportal, & Meltwater, 2025). Users can tag others with "@," "like" and comment on content, and organize topics using hashtags. Since Instagram was only recently made available to businesses, the scholarly research on the platform is still limited. While the initial Instagram studies were shaped by trial and error and best practices (Miles, 2013; Neher, 2013), more recent studies provide deeper insights on the platform's impact on brands. Maulana et al. (2022) emphasize Instagram's cost-effectiveness for fashion businesses - small and medium-sized. According to Wicaksono (2024), Instagram's ability to increase engagement and sales through visually rich content is the reason for its growing popularity across industries. By liking, commenting, or following users, brands engage with consumers and get similar engagement in return (Susanti & Rodhiah, 2023).

Instagram lets marketers talk directly to customers and learn about their motivations through text and, most significantly, pictures. Posts with pictures on Instagram get more engagement than posts with just text on X (Burnell et al., 2021; Díaz et al., 2021), which leads to more interactions (Soonius, 2012). To engage consumers on Instagram, brands mostly employ two tactics: symbolic and emotional (Khan & Raza, 2024; Rietveld et al., 2020). While the symbolic strategy emphasizes the brand's image and promotes its identity or lifestyle, the emotional strategy seeks to influence consumers' affective beliefs associated with product use. Influenced by platform features and interpersonal relationships, consumers interact with UGC to conform to their social identity and self-image (Buzeta et al., 2024).

Compared to X, which focuses on discussions and sharing factual content, Instagram supports the self-focus behavior better (Hu et al., 2022). Furthermore, retweets are usually motivated by informational rather than emotional value (Chung et al., 2020; Saini et al., 2022). Therefore, we propose:

H2: UGC on Instagram (or X) will include more symbolic (or functional) aspects of a product compared to X (or Instagram).

These differences should also be considered in relation to the product type. For utilitarian products, tangible and functional attributes significantly influence attitude formation, while for hedonic products, the intangible and symbolic attributes have a higher impact (Chaudhuri & Ligas, 2006). These findings, in conjunction with those informing H2, suggest that:

H3: For hedonic (but not utilitarian) products, UGC featuring symbolic aspects is more prevalent on Instagram than on X.

H4: For utilitarian (but not hedonic) products, UGC featuring functional aspects is more prevalent on X than on Instagram.

2.3. Brand Sentiment

Marketers know that social media has made it harder for them to influence how people see their brands. This is because brand image is now shaped not just by what the brands say directly (Davenport & Beck, 2018; Esch et al., 2006), but also by what consumers feel and say about them. Indeed, brand sentiment, or valence, is a widely used metric for assessing the impact of social media initiatives (Choi et al., 2021). Sentiment analysis classifies comments as positive, negative, or neutral, where neutral comments reflect objective statements without opinion. To keep the findings more relevant, this study only looks at positive and negative comments and ignores neutral content due to its lack of evaluative sentiment.

Prior research highlights that there are more positive than negative comments, suggesting that consumers generally prefer constructive engagement (Kovacheva et al., 2022; Sukmana & Rusydiana, 2023). Furthermore, regardless of the product type, users are more likely to share practically useful and positive content over negative content (Mishra & Maheswarappa, 2019; Nikjoo et al., 2021). While people often spread negative news more than positive news, social media trends show that positive content tends to be more viral. Prospect Theory offers an explanation. People devote greater cognitive effort to processing negative stimuli due to the positive-negative asymmetry (Kuo et al., 2009). This effort can lead to negative affect (Garbarino & Edell, 1997) and reduced information processing (Glatz & Lippold, 2023), which clashes with the entertainment-oriented nature of social media. Since the main purposes of these platforms are social interaction, escape, and relaxation (Anwar & Mujib, 2022; Kircaburun et al., 2018), we propose that:

H5: Consumers should generate more positive UGC than negative UGC for both utilitarian (H5a) and symbolic (H5b) products on both social media platforms.

Even if positive UGC is predominant on all social media platforms, as highlighted in H5, it is unclear if all platforms share similar proportions of positive or negative sentiment. For instance, is positive sentiment more common on Instagram than on X? Is negative sentiment more prevalent on X compared to other platforms? Zou et al. (2018) discovered that sentiment valence fluctuates by subject, with positive sentiment being more prevalent in tweets about entertainment and lifestyle, while negative sentiment is likely to surround political discussions. Batchelor (2023) and Smith et al. (2012) on the other hand, did not find any persistent changes in sentiment between platforms. It is worth noting, however, that the former focused solely on microblogs like X, while the latter examined comments across multiple platforms, including Facebook, X, and YouTube. Considering both prior findings and the inherent technical and cultural characteristics of each platform, one might expect no major differences in sentiment across sites. Indeed, users can easily post both positive and negative content on platforms like X and Instagram. However, we argue that previous studies may have failed to detect sentiment differences due to the similarity of the product types analyzed. A closer look at products that are predominantly symbolic versus utilitarian may reveal such distinctions. In line with H3, the symbolic attributes of the hedonic products, along with the emotions they evoke, are more effectively expressed through images on Instagram than through text on X. On the other hand, utilitarian products, which

are evaluated by logic and function, are well-suited to textual communication. These evaluations rely heavily on cognitive processing and memory (Hirschman & Holbrook, 1982), making X just as effective a platform for expressing sentiment about utilitarian products as Instagram. Building on research on social media platforms and product type, we propose that UGC for utilitarian products has a consistent sentiment across platforms. For hedonic products, however, we expect sentiment to differ between Instagram and X, such that:

H6: For hedonic products, Instagram will feature more positive sentiment (H6a) as well as more negative sentiment (H6b) than X.

3. Study

3.1. Method

The units of analysis were individual postings collected using the social media monitoring tool Meltwater. The dataset includes X and Instagram posts about selected brands, gathered over a defined 30-day period in June 2018, a time when social media engagement tends to increase due to seasonal shopping patterns and lifestyle changes (Bronner & de Hoog, 2019). Brands were chosen from product categories that represent primarily utilitarian or primarily hedonic consumption.

By specifying brand names as keywords, the time frame, and the target social media platform (for example, X), we compiled a list of qualifying posts. These were delivered by the social media monitoring company in an Excel file and included typical forms of user-generated content for each platform: tweets, retweets, and replies for X; comments and links for Instagram.

To improve the generalizability of our findings, we selected multiple brands within each product category and considered product tangibility. This allowed for comparisons between utilitarian and hedonic products across both tangible and intangible goods. The dataset included four industries: fast food, airlines, cruises, and beer. These categories reflect both product types and tangibility levels. All selected brands were familiar and relevant to consumers' daily lives (see Table 1).

Table 1 (Information about Industries and Brands Chosen for the Study)

Product type		Brand	tweets	Instagram posts
Tangible	Utilitarian	McDonald's	65,536*	4,994
	Hedonic	Heineken	8,200	1,886
Intangible	Utilitarian	Delta Airline	65,536*	3,745
	Hedonic	Royal-Caribbean	8,736	1,180

*Maximum amount of allowed data download was reached

Source: Created by the Authors

The first stage of data analysis was conducted in R Statistical Software (Team, 2013), using several packages for data cleaning and analysis. During cleaning, we removed non-English words, punctuation, URLs, numbers, and common stop words (such as "the," "to," "is," "in"). We retained only words between three and 30 characters, applied stemming, and eliminated sparse words appearing in fewer than 0.1% of cases. We then applied Latent Dirichlet Allocation (LDA), a machine-learning technique designed to manage large-scale textual data. The analysis used the Variational Expectation-Maximization (VEM) algorithm to identify the most frequent terms within dominant topics for each social media platform. Prior research has shown LDA to be highly effective for topic modeling and sentiment analysis in social media contexts (Hammad et al., 2022; Min et al., 2020; Zhao et al., 2021), which supports its selection for this study.

For each brand, we identified the top three topics and the ten terms most strongly associated with each. Each term was manually classified by the authors as symbolic (emotional, experiential, fun, exciting, enjoyable), functional (helpful, useful, practical), or neutral. Classification was done independently by each author, followed by reconciliation of any differences. Terms open to multiple interpretations were categorized as neutral. The final dataset, based on user-generated content from four brands across two platforms, included 24 topics and 240 terms. Of these, 44 terms were classified as neutral, 82 as functional, and 114 as symbolic.

After coding, the data were entered into SPSS under three main variables: social media platform (Instagram or X), brand type (hedonic or utilitarian), and terminology type (functional, symbolic, or neutral).

3.2. Results

A chi-square test of independence showed that there is a significant association between the hedonic or utilitarian character of the brands and the type of UGC related to them, $X^2(2, N = 240) = 23.17, p < .001$. Post-hoc analyses revealed that significantly more terms used in the UGC of utilitarian brands are functional (48.3%) than symbolic (34.2%, $p < .05$), and significantly more terms used in the UGC of hedonic brands are symbolic (60.8%) than functional (20.0%, $p < .05$); thus, supporting our H1a and H1b hypotheses.

When comparing the terminology used in UGC on X versus Instagram, we observe a significant relationship between the platforms and the comment types, $X^2(2, N = 240) = 18.91, p < .001$. Specifically, 60.8% of the terms used on Instagram are symbolic, compared to 34.2% used on X ($p < .05$), and 45.8% of the terms used on X are functional, compared to 22.5% used on Instagram ($p < .05$). These findings help support our second hypothesis.

Hypotheses 3 and 4 require data analyses by brand type. For hedonic products, a chi-square test of independence assessing the relationships between the terminology type and the social media platforms showed no significant relationship between the two variables, $X^2(2, N = 120) = 4.24, p = .12$, thus not supporting our third hypothesis. However, a similar test of independence conducted for utilitarian products revealed a significant relationship between the two variables, $X^2(2, N = 120) = 19.15, p < .001$. As expected, a post-hoc test showed a significant difference between the proportion of functional terms on X (69.0%) and the proportion of functional terms on Instagram (31.0%, $p < .05$). Since these differences were not observed for hedonic products, we conclude that the data support our fourth hypothesis.

To test the fifth and sixth hypotheses, which propose differences in UGC sentiment by brand type and social media platform, we used R Statistical Software with the *syuzhet* package (Jockers, 2023). To enhance accuracy, we analyzed all 159,813 individual comments using four sentiment analysis methods: *syuzhet*, *bing*, *affin*, and *nrc*. Each method assigned a numeric sentiment score, where lower numbers indicated negative sentiment and higher numbers indicated positive sentiment.

Hypothesis 5 proposed that positive comments would outnumber negative ones for both brand types on both platforms. We recoded sentiment accordingly: negative scores were labeled as negative sentiment, zeros as neutral, and positive scores as positive sentiment. Neutral comments were excluded to focus solely on positive and negative feedback.

Using the *syuzhet* method, the number of positive comments was significantly higher than negative comments for both hedonic brands ($X^2(1, N = 14,713) = 5,983.87, p < .001$) and utilitarian brands ($X^2(1, N = 119,624) = 4,970.4, p < .001$) when the data coded by the *syuzhet* method were analyzed. Results from the *bing*, *affin*, and *nrc* methods were consistent, providing full support for Hypothesis 5.

Hypothesis 6a predicted that positive sentiment would be more prevalent on Instagram than on X for hedonic products, while Hypothesis 6b predicted the same for negative sentiment. When comparing sentiment distribution by platform, we found a significant association between platform and comment valence, $X^2(2, N =$

19,993) = 388.19, $p < .001$. Specifically, a higher percentage of the comments were positive on Instagram (76.2%) than on X (57.4%, $p < .05$), supporting H6a. However, we observed a change in directionality for negative comments, with fewer comments on Instagram (6.9%) than on X (14.5%, $p < .05$) being negative, which contradicts H6b.

3.3. Discussion

Our study offers a valuable perspective on how user-generated content differs as a function of the focal product type (utilitarian vs. symbolic) and the social media platform used by the consumers (Instagram vs. X). The findings show that people tend to talk about hedonic products using symbolic and self-expressive language, while utilitarian products are usually described in more practical, functional terms. In addition, the differences seen across platforms indicate that Instagram works better for promoting hedonic products, whereas X is a stronger fit for utilitarian ones. This not only helps understanding consumer behavior on different social media platforms, but can also guide marketers in tailoring their messages to specific product types.

Another important finding involves the sentiment in user-generated content. Although positive UGC was common for both product types, it was not equally distributed between Instagram and X. This suggests that each platform is shaped differently, with unique dynamics that determine how consumers interact with brands.

4. Theoretical contributions

This research significantly enhances the understanding of user generated content (UGC) by validating relationships between product type, platform attributes, and consumer sentiment.

First, it confirms that UGC related to utilitarian products includes predominantly functional terminology, while UGC for hedonic products focuses more on symbolic language. These results build on previous research indicating that conversations about utilitarian products focus more on functionality, while topics about hedonic products elicit more experiential and symbolic responses (Micu et al., 2017). This improves our understanding of how consumers express themselves based on product characteristics.

Second, this study provides insights into behaviors specific to social media platforms. Instagram users tend to focus on symbolic features, while X users tend to focus on functional features. This aligns with studies indicating that different platforms promote different types of UGC and ways of interacting (Schanke et al., 2023). It also confirms that UGC for utilitarian products on X has more functional elements than similar content on Instagram, backing up prior research on platform differences and media richness theory (Basile et al., 2024).

The study also identifies a general positivity bias in UGC across both product types and platforms, supporting claims that online consumer content often carries a positive tone (Nandwani & Verma, 2021). Instagram, in particular, shows more positive sentiment for hedonic products than X, emphasizing how platform culture shapes sentiment, especially for pleasure-driven products (Chen et al., 2024). These insights expand our understanding of consumer engagement and emotional expression across platforms.

Finally, this research offers a strong methodological contribution by combining automated text analysis with manual classification. This hybrid approach provides a reliable framework for examining UGC and can serve as a model for future studies exploring consumer behavior in digital contexts. It ensures a more comprehensive view of the interaction between product type, platform dynamics, and sentiment (Nandwani & Verma, 2021), laying the groundwork for continued research in this area.

5. Practical applications

This research offers explicit direction for marketers aiming to enhance their social media communication strategies. First, companies that sell hedonic products should use Instagram to its full potential, taking advantage of its emotional and self-expressive features. On the other hand, utilitarian products can do better on X, where people are more open to functional and informational messages.

Additionally, the prevalence of positive sentiments in user-generated content suggests that strategies encouraging consumers to create positive content can be highly effective. Marketers should create campaigns that encourage people to have fun and share their experiences on social media in a natural way.

6. Conclusions and recommendations

This study highlights the importance of adapting marketing strategies to both product and social media platform characteristics. We recommend that social media campaigns should be designed with consumer preferences and platform-specific features in mind, particularly focusing on the following actions:

Platform Segmentation. Companies should allocate their resources function of the product type being promoted and the social media platform best suited for that product. On one hand, when promoting utilitarian products, marketers should conduct more marketing campaigns on X and emphasize functional and tangible product features, as UGC on X tends to favor this content (H1a, H4).

On the other hand, hedonic products should be advertised on Instagram through visually pleasing content that emphasizes the product's symbolic and self-expressive qualities (H1b, H2).

Promoting Positive Content. Encourage consumers to create positive user-generated content through interactive campaigns and contests that offer tangible benefits. Design interactive campaigns to encourage consumers to highlight the symbolic aspects of a product, particularly on Instagram, where symbolic and positive sentiment is more prevalent (H6a).

For utilitarian products, create contests on X that encourage users to showcase functional and tangible benefits, such as using a product in everyday scenarios, with rewards like discounts or free upgrades (H5a, H4).

Sentiment Monitoring. Use sentiment analysis tools to track positive and negative sentiment trends for both utilitarian and symbolic products across platforms (H5a, H5b). Closely monitor Instagram UGC for symbolic products as this platform is expected to generate a higher percentage of positive sentiment compared to X, and adjust messaging strategies if sentiment deviates (H6a). Segment UGC based on content type (functional vs. symbolic) and platform, and identify trends that align with or contradict brand expectations (H1a, H1b). Actively respond to and amplify positive UGC while addressing negative feedback swiftly to maintain an overall positive sentiment for both product types (H5a, H5b).

To confirm and expand the results of this research, further studies could examine different social media platforms and even additional product categories. Researchers could take advantage of the remarkably fast evolution of large language models, and study even larger datasets from various social media platforms, drawing more accurate and more profound insights.

7. Acknowledgements

Authors' note on the use of Generative AI

Note: Artificial Intelligence was used only to rephrase some sentences for clarity, readability, and flow. AI was not involved in generating or analyzing scientific content or in developing the research findings.

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