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Topic: A Quantitative Analysis of Social Media Engagement Behaviour from the Perspective
of Uses and Gratifications Theory

Abstract

Social media is an important means of communication, information and opinion for people. It is very important to understand the theories and methods that lead to success for these platforms' content. The Uses and Gratifications (U&G) Theory is adopted in this study to investigate social media engagement behaviour, based on 200 posts from the social media platforms of Facebook, Instagram, and Twitter that are publicly available. The investigation is based on three study goals: understand the engagement level across platforms, explore the engagement of different post types, and understand how sentiment impacts post sharing. The statistical tools used are One-Way ANOVA, Pearson correlation and linear regression. The results show that Instagram and Facebook create far more engagement than does Twitter. Videos and polls are engaging formats for content, and they draw more interaction. Sentiment was marginally correlated with shares, but statistically significant. The results help to build on the body of work on digital engagement behaviour and provide actionable suggestions for content strategists and social media managers.

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1. Introduction: The Importance of the Research

1.1 Background of the Study

Social media is one of the most changing communication areas in the present day. In the last two decades, websites like Facebook, Instagram and Twitter have evolved from niche online communities to a global infrastructure that impacts the way that people seek information, establish identity, build relationships and interact with organisations. By 2024, there will be over 5 billion people using social media around the world, and this figure is still increasing (Statista, 2024). In this massive digital universe, likes, comments and shares have become the currency to measure influence, reach and relevance. As such, it is no longer a concern for marketers or platform designers to understand what leads to engagement, but a core question for anyone interested in how information spreads and how digital behaviour is formed (Voorveld et al., 2018).

Although a lot of research work has been done in this field, there are still some questions which remain unanswered. Many of the previous research studies are descriptive and focus only on patterns of use, rather than causal and associative mechanisms, and are limited to only a single platform, so their findings cannot be generalised to other platforms (Kaplan and Haenlein, 2010). Similarly, theories of social media use have been developed for some time to account for what makes people choose to use social media, but not many have been used rigorously to predict measurable engagement outcomes in relation to the content-level characteristics of social media. This study directly tackles both these limitations: first, by using Uses and Gratifications (U&G) Theory as a unifying theory, and second, by using quantitative statistical methods to test hypotheses across the three major platforms.

1.2 Uses and Gratifications Theory

The Uses and Gratifications approach was formally developed by Katz, Blumler, and Gurevitch (1973), which is based on a relatively simple yet potent idea: the audience does not passively receive messages from the media. People select the media they consume, and they select them to meet certain psychological and social needs. These needs in the social media space could mean needs for entertainment, information, social interaction, self-expression, or identity construction (Whiting and Williams,

2013). Realistically, this implies that the content attributes of a post, its format, its tone of voice, and where it is posted are not incidental. They find out if the content matches the gratification which a person brings to scrolling. With strong alignment comes engagement. If it is low, then the content is ignored.

This reasoning leads to a well-defined set of testable expectations. Thus, in the event that Instagram's visual-centric design offers greater gratifications of modality and entertainment than Twitter's text-centric design, then Instagram should generally achieve greater levels of engagement (Sundar and Limperos, 2013; Tsai and Men, 2013). When a user can interact with the content on the page and be stimulated by some interactive or audiovisual element (such as a poll, video, etc.), it should drive more likes, comments and shares than a text post. When there is emotionally charged content that evokes higher psychological arousal, from positive warmth and negative provocation, there should be an observable impact on the sharing of content across networks (Brady et al., 2017). Formalising each of these expectations in the form of a research hypothesis and testing them empirically in this research.

This theory is suitable for this study because it explains why people choose and engage with different types of social media content. It also helps to understand how users satisfy their needs for information, entertainment, and social interaction through different platforms. In addition, the theory provides useful guidance for content creators and marketers by suggesting that content should be designed to meet users' needs and interests to increase engagement (Bhatiasevi, 2024).

1.3 Significance of the Study

This research is very applicable. In numerous of the world's largest economies, social media advertising and content investment have outpaced investment in traditional media spending (eMarketer, 2024). Whether it's big companies or small, or even someone who is just an individual content creator, there are many businesses out there that invest time and money into creating social media content in hopes that it will sell without realising that they don't always possess a clear understanding of what will make it sell, and they don't have the evidence to prove it. Platform algorithms encourage engagement by showing more people posts that get more engagement,

which further increases engagement. Understanding factors that drive engagement is critical and increasingly important in the context of how content is quality-checked, how it makes them feel, and how it is amplified. The results of this research have implications for content strategy, resource allocation and campaign planning in sectors (Ruggiero, 2000).

1.4 Research Aim

The aim of this study is to examine the factors of social media engagement behaviour using a quantitative method based on uses and Gratifications Theory.

1.5 Research Objectives

1. To evaluate engagement levels among diverse social media platforms.
2. To compare total engagement levels across different post types.
3. To examine the effect of sentiment on number of shares.

1.6 Research Questions

- ❖ What is the difference level of engagement among various social media platforms?
- ❖ Are there significant differences in total engagement levels across different social media post types?
- ❖ Does sentiment substantially affect likes, comments, and shares?

1.7 Structure of the Dissertation

This report proceeds in the following way. In Section 2, a critical review of the literature, the conceptual framework and the statements of the research hypotheses are presented. The research methodology is described in section 3, which comprises philosophical background, research design, sampling, variable operationalisation and analytical process. The data analysis process follows the data analysis process in the sense of the full description of the descriptive data, assumption check, and the result of the hypothesis test is reported in Section 4. The results and conclusions are presented in section 5, including theoretical contributions, practical implications and the limitations of the study. In Section 6, a reflective essay is provided that explores how the module has enhanced competencies in quantitative research and reflection

on the suitability of quantitative research methods for the wider DBA research journey.
Complete bibliographic citations and appendices are at the end.

2. Literature Review, Conceptual Framework, and Hypotheses

2.1 Social Media Engagement: Definitions and Dimensions

The term social media engagement is widely used, but it has different meanings in different studies. Recent research generally measures engagement through users' visible actions, such as likes, comments, and shares (Mardhatilah et al., 2024). These actions represent different levels of user interaction. Likes usually to show basic engagement, comments reflect deeper interaction, and shares indicate that users want to spread content to others (Yip et al., 2024). Together, these actions are commonly used to measure overall social media engagement.

Sbaffi and Rowley (2017) suggest that engagement can be viewed as a form of digital capital because content that receives higher engagement is more likely to gain greater visibility through social media algorithms. Recent studies also show that user engagement plays an important role in increasing content visibility and interaction across different social media platforms (Avalle et al., 2024).

Recent research has also explained that user engagement can be either passive or active. Passive engagement, such as liking a post, requires less effort, while active engagement, such as commenting or sharing, reflects greater user involvement (Peters et al., 2024). This difference is important for the present study because it examines how post type and sentiment influence different forms of engagement across social media platforms.

2.2 Uses and Gratifications Theory in the Context of Social Media

Uses and Gratifications (U&G) Theory originated from early media studies and was first introduced by Lazarsfeld and Stanton (1944) before being formally developed by Katz et al. (1973). The theory argues that people actively choose media to satisfy their psychological, social, and cognitive needs rather than passively receiving media messages. This perspective considers users as active decision-makers who select

different media based on their personal goals and expected benefits. Although the theory was originally developed for traditional media, it has become one of the most widely used theoretical frameworks for explaining user behaviour on social media platforms (Katz et al., 1973; Kircaburun *et al.*, 2024).

The rapid growth of social media has increased the relevance of U&G Theory because users are no longer only consumers of information but also creators and distributors of content. Users engage with social media to satisfy different needs, including information seeking, entertainment, social interaction, self-expression, relationship maintenance, and communication. These motivations influence how users interact with online content through liking, commenting, sharing, and content creation. Recent studies continue to confirm that users' motivations are important predictors of engagement behaviour across different social media platforms (Bauer and Tian, 2024).

Whiting and Williams (2013) identified ten major motivations for social media use, including social interaction, information seeking, entertainment, relaxation, communication, convenience, opinion expression, information sharing, and surveillance. Similarly, Smock et al. (2011) argued that user motivations differ not only across platforms but also across individual platform features. More recent empirical evidence also indicates that content characteristics, media format, and user motivations are all important factors that affect the engagement outcomes, which means that U&G Theory is still highly relevant in the context of explaining social media interaction (Hoang, Tran and Le, 2024).

Sundar and Limperos (2013) added new gratifications related to Web 2.0 technologies in U&G Theory: agency, interactivity, navigability, and modality. Of these, modality is important as users will be reacting to text, pictures, videos and interactive content. Recent studies reveal that the higher the level of media and the more user-centric the content, the more likely there will be reactions, comments and sharing. This makes U&G Theory a solid theory to explain the different level of engagement between different content formats (Hoang, Tran and Le, 2024).

Quan-Haase and Young (2010) examined the uses of Facebook using U&G Theory and concluded that the primary motives for using Facebook were for passing the time and social entertainment, while IM services were primarily used for fulfilling

communication needs. Recent research also shows that different platforms are used for different motivations, leading to platform-specific engagement behaviours. Engagement, therefore, is likely to differ between the platforms of Facebook, Instagram, and Twitter, which gives theoretical justification for comparing user engagement across the platforms in the current study (Bauer and Tian, 2024).

2.3 Platform Differences in Engagement

The number of social media interactions can differ based on the different social media platforms, technological features, content types, algorithms, and user motivations. These platform-specific qualities help shape the way users engage with content, and the degree to which they engage with it on each platform. Recent studies indicate that platform design and user motivations can influence a user's engagement behaviors, and there are considerations for cross-platform comparisons to understand social media performance (Masciantonio et al., 2023; Pang, Ruan and Wang, 2024).

Instagram is known for its high engagement rate since it is a social media platform focused on visual content such as images, short videos, stories and reels. Its visual interface and recommendation system help users like, comment, save, and share their content more often. Facebook, on the other hand, has a wider variety of content types, such as text, images, video, links, and community-based interactions. While the engagement mechanisms are different than Instagram, Facebook still has a high number of interactions due to their wide variety of content and community features (Chen, Pham and Tran, 2024; Pang, Ruan and Wang, 2024).

Twitter mainly focuses on real-time communication, news, and public discussions through short text-based posts. While Facebook and Instagram rely heavily on visuals to drive engagement, Twitter's engagement is more heavily driven by information sharing, public conversations and current events. Research comparing multiple social media platforms has shown that users have different motivations for using Facebook, Instagram, and Twitter, resulting in significant differences in engagement patterns across these platforms (Masciantonio et al., 2023; Alhabash et al., 2024).

These results suggest that each platform provides different types of interaction and meets different user's needs, which leads to different usage behaviors. This means

that the engagement rates will vary between Facebook, Instagram, and Twitter , offering theoretical and empirical evidence for Hypothesis 1 of the present study.

2.4 Post Type and Content Format Effects

One of the most acknowledged factors to impact social media interaction is content format. Recent research indicates that there are different responses to the use of the different posts due to the different degrees of visual appeal, information richness and interaction opportunities afforded by each post. Generally, posts with images, videos, or interactive elements tend to be more engaging than those with only text, as images and videos tend to capture the attention of users and encourage them to interact with the content (van der Harst and Angelopoulos, 2024; Yip et al., 2024).

Across all social media platforms, increased engagement has always been related to visual content like images and videos. As revealed by recent studies, images attract more attention from users and videos bring more information and make users stay longer to interact with content. Poll, quizzes, and carousel posts are other interactive formats that boost engagement as users are more likely to interact with the content than just read it. These features cater to the users' desires for self-expression, involvement, and social interaction, which are core ideas in the Uses and Gratifications Theory (Yip et al., 2024; Wang and Xin, 2026).

The effectiveness of various post types can also be different depending on the social media platform, as each one prioritizes content in different ways. Carousel posts and short-form videos tend to do well on platforms like Instagram, for instance, while text-based posts may garner less engagement. This means that the same type of content can yield varying levels of engagement on different platforms (van der Harst and Angelopoulos, 2024; Wang and Xin, 2026).

The data set of this study consists of five post types (text, image, carousel, poll, video). An analysis of engagement of such formats can help in the examination of whether there are any significant differences in levels of engagement between content types and social media platforms.

2.5 Sentiment and Sharing Behaviour

Social media engagement and content sentiment have a complex theoretical and empirical relationship. It has been proposed that generally, emotional content, as opposed to neutral content, with a high level of arousal tends to elicit higher level of engagement (see Circumplex (Arousal–Valence) Model of Emotion (Russell, 1980). Recent research corroborates this by demonstrating that emotionally stimulating content has garnered substantially more reactions, comments and shares on social media compared to emotionally neutral content (Brady et al., 2023; Bhargava et al., 2024). Brady et al. (2023) also showed that the intensity of emotions, not just the positive or negative sentiment, is a better predictor of content sharing on social media.

Other studies however have provided evidence for valence-specific effects. Positive content was more likely to be shared than negative content, as it was likely to strengthen one's positive image in one's social network as a means of social impression management (Berger and Milkman, 2012). Some more recent research indicates that sharing behaviour can be boosted by both positive and negative emotions, albeit under certain conditions: context of the communication, characteristics of the platform, and expectation of the audience (Bak, 2026).

Positive emotions, for instance, may lead to engagement with lifestyle and brand-related content, while negative emotions like fear or anger are more likely to spark engagement with political events, crises, or public debates (Bak, 2026).

Recently, quantitative studies have tried to address this paradox by subdividing negative sentiment into different emotional categories. Recent studies reveal that negative emotions like fear, anger, sadness, and anxiety have different impacts on user engagement: not all negative emotions are created equal. The research suggests that the emotional arousal is the core driver for content spillover as opposed to the emotional direction alone (Bhargava et al., 2024; Brady et al., 2023). Sentiment metric scores like the one in this data set are based on a combination of positive, neutral and negative sentiment. Hence, sentiment scores can be analysed to gain a reality check on the effect of emotional content on sharing behavior. If there is a negative correlation between sentiment score and shares then this would indicate that lower (more

negative) sentiment scores correspond to higher levels of sharing, as suggested by the arousal driven sharing hypothesis.

2.6 Research Gaps

While there have been significant contributions to the understanding of social media engagement in previous studies, there are still a number of research gaps. Firstly, most quantitative studies have been conducted on a single platform like Facebook, Instagram, or Twitter, and it's challenging to compare the engagement across platforms in the same framework. Consequently, it is not always possible to extrapolate the results to other social media.

Second, although the Uses and Gratifications (U&G) Theory has been widely applied to understand and explain the reason why users use social media, few studies have employed the theory to analyze the differences between the platforms, the type of posts, and the sentiment simultaneously in one research model.

Third, previous studies have mainly examined the effects of post type or sentiment separately. There is limited research that has examined how these factors interact with one another, when taking into account the platform as a contextual factor.

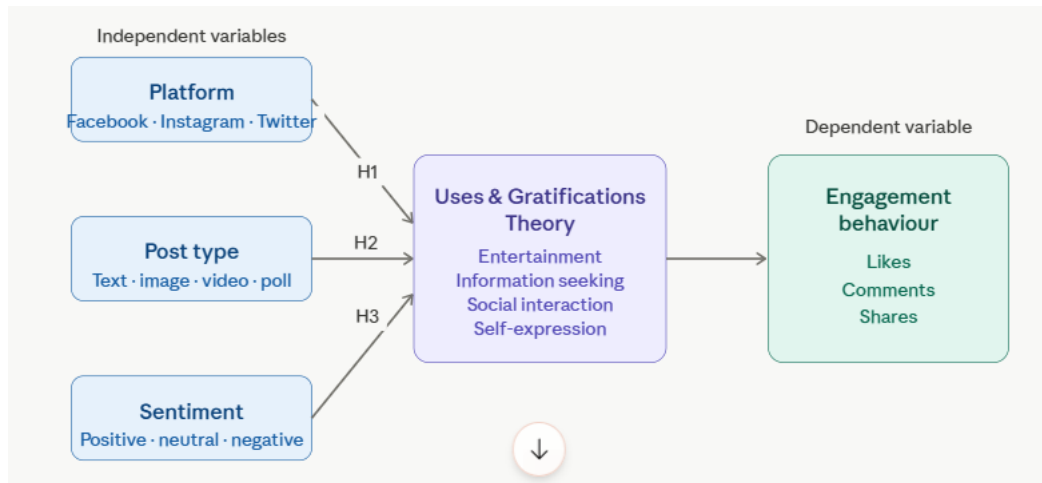
This study fills those gaps by exploring how user engagement differs across Facebook, Instagram, and Twitter and how integration of platform, post type, and sentiment influences user engagement within the framework of the Uses and Gratifications Theory. This is expected to give a more detailed picture of people's social media engagement.

2.7 Conceptual Framework and Hypotheses

The conceptual framework will be used as the overarching lens through which the content-level characteristics (post type and sentiment) and structural characteristics (platform) will be predicted to affect the engagement behaviour (likes, comments, and shares). It is based on the idea that various platform environments create different

profiles of gratification, and that the attributes of the content indicate the possibility of gratification fulfilment and, in turn, which gratification responses will be more likely.

H1: There is a significant difference in total engagement levels across social media platforms (Facebook, Instagram, and Twitter).



H2: There is a significant difference in total engagement levels across post types (text, image, carousel, poll, and video).

H3: Sentiment score has a significant relationship with social media sharing behaviour.

H3a: The number of shares is significantly predicted by sentiment.

Figure 1: Conceptual framework

3. Research Methodology

3.1 Research Philosophy

This study is grounded in a positivist epistemological position. In positivism, the social world can be analysed objectively by means of measurement, and causal or associative relationships can be determined by making systematic observations and statistical analysis (Saunders et al., 2019). This philosophical approach is very suitable for the present study, which aims to find patterns and to test hypotheses on engagement behaviour by means of numerical data. A realist ontological view is taken that assumes that engagement measures are real behaviour measures that can be measured and compared to other contexts (Creswell and Creswell, 2018).

The positivist perspective is in favour of a deductive approach to reasoning, which begins with theoretical propositions based on U&G theory and previous empirical studies, and then proceeds to testing these propositions with actual data. This is in line with the classical scientific approach of hypothetical deductive method, which is largely used in doctoral-level business and management research (Bryman and Bell, 2015; Goh et al., 2013).

3.2 Research Design

This study is a quantitative, cross-sectional study. A cross-sectional design is suitable to get a snapshot of a phenomenon at a specific point in time, and when the research analytical objective is to compare groups or investigate associations (Hair et al., 2019). Social media data was gathered over a 1-year period (2023), and therefore, some temporal representation can be found in the data, without sacrificing efficiency and replicability of secondary data analysis.

The secondary data method has been widely used and accepted in quantitative social science research, provided that primary data collection would be difficult or problematic logistically or ethically (Bryman, 2016). First, the direct access to user-level data from social media platforms is an ethical issue, as is privacy. Second, the access to secondary data (anonymised) from social media platforms avoids the ethical and privacy issues and still allows for the testing of hypotheses.

3.3 Data Source and Description

A total of 200 social media posts were obtained from the Kaggle repository (Divya Raj, 2025) from three large social media platforms: Facebook (n = 64), Instagram (n = 72), and Twitter (n = 64). The following variables are included in each observation: platform, post type, post day, post time, number of likes, number of comments, number of shares, total engagement (the sum of likes, comments and shares), and sentiment score. The sentiment variable is represented as a categorical variable (positive, neutral, negative), and it is also presented as a numeric value (positive = 3, neutral = 2, negative = 1) in case the sentiment needs to be analysed as a continuous variable.

Post type represents a number from 1 to 5, indicating the following post types: 1 = text, 2 = image, 3 = carousel, 4 = poll, and 5 = video. This coding system allows for the comparison of three or more groups by ANOVA and the interpretation of data in an ordinal fashion, when possible. The dependent variables for Objectives 1 and 2 are total engagement, and for Objective 3 are shares.

3.4 Sampling

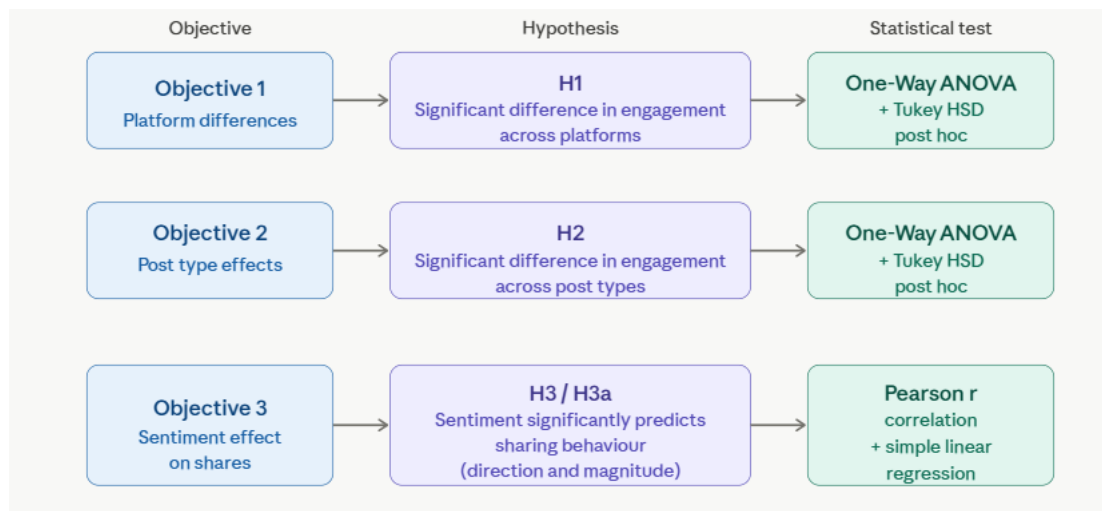


Figure 2: Analytical framework

This sample of 200 posts was obtained by the provider of the dataset, who used a purposive, non-probability sampling method, according to the following criteria: Viral or trending posts across the three platforms during 2023. Theoretically, probability sampling would be used to achieve generalisation of findings, given the fact that it would be impractical to do so with all posts on social media and with the exploratory and illustrative nature of the study, purposive sampling is an acceptable method

(Patton, 2002). The sample size of 50 observations per group for each platform is sufficient to have adequate statistical power in making ANOVA-based comparisons as recommended by Field (2018).

Retrospective power analysis was conducted to determine the size of the sample needed to detect medium effect sizes ($\alpha = 0.05$). The number of (200) samples required to obtain a statistical power of more than 0.90 (more than good) for ANOVA with three groups and a medium-sized effect ($f = 0.25$) (Cohen, 1992).

3.5 Variables and Operationalisation

The operationalisation is a procedure that transforms theory into measurable variables (Bryman and Bell, 2015). For this study, engagement behaviour is measured as three different types of engagement: likes (passive affirmation), comments (active participation), and shares (content propagation). These are collated to give a total engagement score to Objectives 1 and 2.

Platform is a categorical variable with three categories (Facebook, Instagram and Twitter). Post type is nominal level data with 5 categories (text, image, carousel, poll, video) that are coded numerically as 1-5 in the data set. Sentiment is operationalised as a numeric score (1 = negative, 2 = neutral, 3 = positive), which allows it to be used in correlation/regression analysis.

3.6 Analytical Approach and Statistical Tests

The analysis of all the data was carried out by IBM SPSS Statistics (Version 29). Three analytical techniques were used according to the objective of the study and the type of variables.

One-Way ANOVA (Objectives 1 and 2): To test for significant differences in mean total engagement between the platform groups (Objective 1) and the post type groups (Objective 2), One-Way ANOVA was used. ANOVA can be used in situations where there are three or more independent groups and the dependent variable is measured at the interval or ratio level (Field, 2018; Smith et al., 2012). To validate the results of the ANOVA, the following assumptions were checked: normality (Shapiro-Wilk test and inspection of histogram); homogeneity of variance (Levene's test). Wherever the assumptions were generally fulfilled, the parametric ANOVA test was used as the main

test. To determine specific pairwise differences between groups, an Honest Significant Difference (HSD) post hoc test was used by Tukey.

Pearson's Correlation (Objective 3): The linear association between sentiment score and shares was assessed by using Pearson's r . This test can be used when both variables are on an interval scale, and it is hypothesised that the relationship between the two is linear (Pallant, 2020). The strength of the correlation was categorised as small ($r = 0.10$), medium ($r = 0.30$) and large ($r = 0.50$) based on Cohen's 1988 benchmarks.

Simple Linear Regression (Objective 3a): After conducting analysis for correlation, simple linear regression was modelled to measure the explanatory power of the sentiment towards the number of shares. Regression is a formal elaboration on the concept of correlation, which gives an estimate of effect size (the standardised beta coefficient), as well as predictions of a dependent variable from an independent variable (Field, 2018). The coefficient of determination or R-squared value was used to determine what percentage of the variance in shares is accounted for by sentiment.

3.7 Ethical Considerations

The secondary dataset used in this study is publicly available and anonymised which reduces a number of the common ethical issues associated with informed consent, participant privacy and data protection. The data set contains no identifiable people. The study adheres to the data governance principles of the UK Data Protection Act (2018), and the ethical guidelines of the University of Wales Trinity Saint David.

4. Data Analysis

4.1 Descriptive Statistics

The data set is first described prior to testing the hypotheses. The sample comprises 200 social media posts: 64 (32%) Facebook, 72 (36%) Instagram and 64 (32%) Twitter. Post types are distributed as follows: post type 1 (text, $n = 42$), post type 2 (image, $n = 34$), post type 3 (carousel, $n = 52$), post type 4 (poll, $n = 26$), and post type 5 (video, $n = 46$). The distribution of sentiment is fairly even between positive ($n \approx 70$), neutral ($n \approx 64$) and negative ($n \approx 66$) categories.

The mean total engagement across the full dataset is $M = 3,000.12$ ($SD = 1,769.10$). This number is a summary of a lot of variation in platforms and post types, and is what the following hypothesis tests aim to explain. As with many findings, the mean number of likes is higher than that of the mean number of shares or comments, and this is in line with prior research that shows “passive” forms of engagement (likes) are more prevalent than “active” forms (shares, comments) across platforms (Boyd & Ellison, 2007). Below is a summary of descriptive statistics of engagement for each platform (Table 1).

Table 1: Descriptive Statistics for Total Engagement by Platform

Platform	N	Mean	Std. Deviation
Facebook	64	3,423.03	1,713.65
Instagram	72	3,757.44	1,746.26
Twitter	64	1,725.22	1,012.07
Total	200	3,000.12	1,769.10

4.2 Objective 1: Platform Differences in Engagement (H1)

A One-Way ANOVA test was used to test if there was any significant difference between total engagement for Facebook, Instagram and Twitter. As shown in Table 1, Instagram posts had the highest mean engagement ($M = 3,757.44$, $SD = 1,746.26$), followed by Facebook ($M = 3,423.03$, $SD = 1,713.65$) and Twitter ($M = 1,725.22$, $SD = 1,012.07$). It's quite eye-catching and starkly different – especially from the perspective of Twitter.

The ANOVA results (Table 2) support that the difference between the groups is statistically significant, $F(2, 197) = 33.133$, $p < .001$. Effect size was determined by eta-squared (η^2), which was determined to be .252, which shows a large practical effect (Cohen, 1988). This represents about 25% of the overall variance in engagement.

Table 2: ANOVA Results – Platform and Total Engagement

Source	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	156,765,438.47	2	78,382,719.23	33.133	.000
Within Groups	466,046,246.65	197	2,365,716.99		
Total	622,811,685.12	199			

Post hoc comparisons using Tukey HSD were conducted to determine which were significantly different when performing this analysis (Table 3). Tukey HSD post hoc comparisons revealed that Twitter was significantly different from both Facebook (mean difference = 1,697.81, $p < .001$) and Instagram (mean difference = 2,032.23, $p < .001$). The difference between Facebook and Instagram was not statistically significant, though (mean difference = -334.41, $p = .416$). This suggests that the main platform split is between the image-centric platforms and Twitter.

Table 3: Tukey Post Hoc Comparisons – Platform

Comparison	Mean Difference	Sig.
Facebook vs Instagram	-334.41	.416
Facebook vs Twitter	1,697.81*	.000
Instagram vs Twitter	2,032.23*	.000

From the results, it is concluded that H1 is supported. Statistically, there is a difference in engagement between them and Instagram and Facebook both have significantly more engagement than Twitter.

4.3 Objective 2: Post Type and Engagement (H2)

To determine if there were differences in total engagement for five post types, a second One-Way ANOVA was conducted. Descriptive statistics (Table 4) show that poll-based content (post type 4) had the highest mean engagement ($M = 3,746.38$, $SD = 1,702.91$), followed by video content (post type 5, $M = 3,542.78$, $SD = 2,077.66$). Text posts (post type 1) had the lowest mean engagement ($M = 2,228.62$, $SD = 1,127.44$).

Table 4: Descriptive Statistics for Total Engagement by Post Type

Post Type	Format	N	Mean	Std. Deviation
1	Text	42	2,228.62	1,127.44
2	Image	34	2,601.47	1,637.97
3	Carousel	52	3,030.73	1,754.18
4	Poll	26	3,746.38	1,702.91
5	Video	46	3,542.78	2,077.66
Total		200	3,000.12	1,769.10

The ANOVA (Table 5) returned a statistically significant result, $F(4, 195) = 5.052$, $p = .001$. The eta-squared was .094, which is considered a medium/large effect. The variance of engagement due to post type accounts for about 9.4% of engagement variability.

Table 5: ANOVA Results – Post Type and Total Engagement

Source	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	58,476,914.53	4	14,619,228.63	5.052	.001
Within Groups	564,334,770.59	195	2,894,024.47		
Total	622,811,685.12	199			

For the Tukey post hoc tests, two statistically significant differences were found between the post types: post type 1 (text) and post type 4 (poll) (mean difference = -1,517.77, $p = .004$);

and post type 1 (text) versus post type 5 (video) (mean difference = -1,314.16, $p = .003$). The other pairwise comparisons were not statistically significant. This conclusion matches the results of the other formats, confirming that the text post format gets much less engagement than the poll or video format.

Table 6: Tukey Post Hoc Comparisons – Post Types (Selected Significant Pairs)

Comparison	Mean Difference	Sig.
Type 1 (Text) vs Type 4 (Poll)	-1,517.77*	.004
Type 1 (Text) vs Type 5 (Video)	-1,314.16*	.003

Using these results, the hypothesis of H2 is supported. Total engagement was found to be significantly affected by interactive, audiovisual-type content, having the most engagement with users.

4.4 Objective 3: Sentiment and Sharing Behaviour (H3 and H3a)

4.4.1 Pearson Correlation

A Pearson correlation was conducted to examine the relationship between sentiment score and shares. The analysis produced a statistically significant weak negative correlation ($r = -0.283$, $p < .001$). This indicates that posts with more negative sentiment tended to receive slightly more shares than posts with more positive sentiment. Although the relationship is statistically significant, its strength is weak, suggesting that sentiment alone explains only a small proportion of sharing behaviour. Other factors, such as topic relevance, audience interest, timing of the post, or content quality, may also influence sharing behaviour.

Table 7: Pearson Correlation – Sentiment Score and Shares

Variables	Pearson r	Sig. (2-tailed)
Sentiment Score & Shares	-0.283	.000

From this result, H3 is supported. Sentiment is negatively associated with the number of shares, with a statistically significant relationship.

4.4.2 Linear Regression

A simple linear regression was estimated using sentiment score as the predictor and shares as the dependent variable to see if sentiment could predict shares. The model was statistically significant, $F(1, 198) = 17.265$, $p < .001$, with an R^2 value of .080. Whilst these results are modest, but not insignificant, they represent about 8% of the variance in sharing behaviour, a significant result in a real-world social media setting where many factors would normally be used to explain the variance in sharing.

Table 8: Regression Model Summary

R	R Square	Adjusted R Square	Std. Error of Estimate
0.283	0.080	0.076	272.256

Table 9: Regression Coefficients

Predictor	B	Beta	t	Sig.
Constant	672.38		6.21	.000
Sentiment Score	-96.03	-0.283	-4.155	.000

The unstandardised regression coefficient for sentiment ($B = -96.03$) means that a one-unit increase in sentiment score (from a negative to neutral score, or from neutral to positive) results in a corresponding decrease of about 96 in the number of shares. As in simple regression, the standardised beta ($\beta = -0.283$) is the same. Based on these results, H3a is supported. Sentiment has a strong predictive effect on sharing behaviour; 8% of the variance is explained.

5. Findings and Discussion

5.1 Findings

Objective 1 – Platform Differences

The overall engagement (total) differed significantly between social media platforms, $F(2, 197) = 33.133$, $p < .001$, $\eta^2 = .252$. Instagram and Facebook have much higher engagement than Twitter. This aligns with the results of previous studies, which revealed that Instagram tends to foster more engagement with users compared to Facebook and Twitter, primarily due to its visual nature and interactive elements (Romero-Jara et al., 2024).

The finding is also consistent with the Uses and Gratifications Theory, which posits that users make a conscious decision to use social media platforms that better meet their communication, entertainment, and social gratification needs (Sundar and Limperos, 2013).

The findings also suggest that the platform itself is an important factor influencing engagement. The same content can be shared on different platforms, but users' reactions are not necessarily similar. This could be due to the fact that each platform offers unique features, user behaviour, and ways of communication, impacting how users interact with content.

In general, this is consistent with current literature. But this research offers further proof, conducting a comparative study of Facebook, Instagram, and Twitter with the same data set and statistical analysis. This direct comparison helps to give a better understanding of the impact of platform differences upon user engagement, and the need to take into account platform characteristics when designing social media strategies.

Objective 2 – Post Type Effects

The one-way ANOVA showed statistically significant differences between the total engagement of the various post types ($F(4, 195) = 5.052$, $p = .001$, $\eta^2 = .094$). This revealed that polls and video posts were receiving the greatest engagement by users, with text and image posts having comparatively lower engagement.

This aligns with recent empirical research indicating content format can have a significant impact on social media user engagement. Xu, Chen and Ow (2023) indicated that the characteristics of the post such as vividness and interaction have a significant positive effect on users' likes, comments and shares as it gains more users' attention and more participation from the user. Likewise, Thorgren, Mohammadinodooshan and Carlsson (2024) found that various types of content on Instagram encourage different user engagement and that the visually rich and interactive content types are better for sustaining engagement than static posts. This aligns with the current study, in which polls and videos garnered significantly more engagement compared to text and image posts.

The results can also be understood by the Uses and Gratifications Theory (UGT). Users purposefully choose to view content that meets their need for entertainment, information, interaction and participation. Video posts are both visually appealing and easier to digest; they include video and audio features, and polls invite users to directly give their opinion. This means that post types bring more satisfaction, which results in more engagement than old fashioned textual content.

Based on the effect size ($\eta^2 = .094$), it can be inferred that the post type is considered a fairly strong predictor of user engagement. While there may be other factors that play a role, the structure of the content itself is a meaningful factor in the way users engage with the content. So, organisations, marketers and social media managers need to be mindful of the right content formats for maximum engagement.

This is also relevant to the literature as it offers empirical evidence from a comparative study of four types of posts and leverages the same data. This study is the first to directly compare text, image, video and poll posts, as previous studies have focused on a single type of content or a single platform, and then analyzed using different statistical methods. This provides a clearer understanding of how different content formats influence engagement and offers practical guidance for organisations seeking to enhance their social media communication strategies.

Objective 3 – Sentiment and Sharing Behaviour

Statistically significant negative correlation was found between sentiment score and the number of shares as measured by Pearson correlation analysis ($r = -0.283$, $p <$

.001). In addition, the simple linear regression analysis showed that sentiment score significantly predicted sharing behaviour ($R^2 = .080$, $F(1,198) = 17.188$, $p < .001$). The negative regression coefficient means that the more negative the sentiment, the more shares are being traded. The model accounts for 8% of the variance between sharing behaviour and this relationship is statistically significant resulting in the rejection of the third null hypothesis.

This is in line with previous empirical studies that have demonstrated that negative information is more likely to be shared than positive information on social media. This is what Watson et al. (2024) did by examining more than 95,000 online news articles and more than 579 million Facebook and Twitter posts and determine that users were almost twice as likely to share negative news than positive news. Their findings indicate that negative emotions do have greater attention grabber and that they drive people to share further content in their social networks.

Similarly, Cheng and Li (2024) found that TikTok videos with more negative sentiment led to significantly higher levels of the present finding.

of audience engagement, such as sharing behaviour. According to their study, content with emotional appeal is more likely to elicit users' response and promote the diffusion of content on social media.

The Uses and Gratifications Theory (UGT) can be used to explain this result. Users select, consume and share content that meets their psychological and social needs (Sundar and Limperos, 2013) according to UGT. Negative content tends to evoke more emotional reaction, curiosity and sense of importance, and encourages users to share content with others. In a lot of cases users share bad contents not just for their own opinions but also to warn, inform or to provoke discussion of their social networks.

While this regression model accounts for only a small amount of variance ($R^2 = .080$), this is normal for social media research since there are many factors that affect user engagement, such as content quality, platform algorithms, the time of day the post was made, audience attributes, and media type. Sentiment, however, should not be treated as the sole determinant for sharing behaviour and should be regarded as an important indicator.

Overall, this research contributes to the literature that has shown that the emotional tone can affect the spread of information on social media. Meanwhile, this research is an expansion of the previous research, which examined the relationship between sentiment and

Comparing sharing behaviour through one data set on various social media, and correlation and regression analyses. The results offer marketers, organisations and communication professionals valuable, real-world data on how emotional tone is important to consider when creating social media content aimed at maximising reach and sharing.

5.2 Theoretical Contributions

There are a number of contributions made to the literature from this study. First, it shows that the U&G Theory can be used to understand and explain engagement differences across multi-platform, and goes beyond usage behaviour to the nature of interactions and outcomes. Second, it offers quantifiable evidence for a modality gratification theory of the impact of content format on engagement proposed by Sundar and Limperos (2013). Third, the dataset-level finding is an addition to the mixed literature of sentiment and sharing, as it supports the arousal hypothesis, with evidence of that effect even in a multi-platform (including both Facebook and Twitter) and multi-categories sample.

Overall, the findings support the main idea of the Uses and Gratifications Theory. The results show that people actively choose social media content that meets their needs, such as information, entertainment, and social interaction. This study also found that engagement is influenced by the social media platform, content format, and emotional tone. These findings are consistent with the Uses and Gratifications Theory, which explains that people engage more with content that satisfies their needs and interests (Bhatiasavi, 2024).

5.3 Practical Implications

The results are clearly applicable to the practice of social media. If content managers want to boost engagement, it's important to understand that engagement is different across platforms: Instagram and Facebook posts enjoy significantly higher engagement rates than tweets. This differential should be taken into account when making choices over the allocation of resources. The data overwhelmingly points to the conclusion that interactive and audiovisual content (polls and videos) performs better than text-based posts, in terms of format. For organisations with a smaller number of content creation resources, video and interactive content may be the best choice, even if they do not have the time to create as many posts.

The sentiment data should be interpreted cautiously since the more negative material there is, the more shares there are. The negative framing may appear to be a good strategy for increasing the virality of a message, but other research, like that conducted by Brady et al. (2017), warns that excessive negative information could eventually damage consumers' trust in brands. A more subtle approach, focusing on emotional depth and salience, rather than negativity, is likely to be more enduring.

5.4 Limitations

This study has some limitations which should be noted. Firstly, the data set is small (only 200 posts) and may not be representative of the overall larger population of social media posts. Although the purposive sampling method was suitable for this study, it restricted the findings to the generalisation of the findings in the statistics. Second, it is a single year (2023), and the use of social media is dynamic, so the results may differ during other time periods. Thirdly, the sentiment variable is a composite score without distinguishing between different types of positive or negative sentiments, restricting the theoretical precision.

Fourth, this research did not adjust for other potential confounding factors, like the use of hashtags, influencers' status, time of publication and platform algorithm updates. The models presented here account for only a small fraction of the variance, and engagement is a function of numerous factors. Future studies should include multivariate designs that provide for estimating the effects of the content, platform and poster characteristics simultaneously.

5.5 Future Research Directions

The work could be continued in several directions in the future. A longitudinal design would enable researchers to examine the changes in engagement dynamics over time, especially with regard to platform algorithm updates. If we can consider the posts as levels within platforms and platforms as levels within users, then modelling this would allow for the multi-level model to be used. Content analysis or the analysis of interview data could be used in qualitative complementarity studies to shed light on the motivational processes which underlie the activation of engagement responses to particular content formats or sentiments, which are lacking when considering only quantitative data.

6. Reflective Essay

At the beginning of this module, I thought I had a good understanding of research. I was familiar with academic papers, statistics in reports, and presenting arguments numerically in the workplace. The module, however, gave me a sense of there being a significant gap between knowing what statistics are and knowing how to do proper quantitative research. The module had a challenging academic impact and was a shift in my thinking of evidence, data and research design.

I knew I had the confidence to start the module at the beginning because my work environment was data-oriented, and I had some knowledge of statistics. I understood concepts such as averages, percentages, and simple graphs. I had also read regression results and surveys conducted in industry reports. But, after the first couple of weeks of the module, it dawned on me that I knew the bare bones of it, but not much more. I learned some statistics, but I had no real understanding of statistical procedures, statistical reasoning or the meaning of assumptions at the doctoral level; and I was not properly taught in those areas. I knew that to use statistics as evidence, a lot more critical thinking was involved than just presenting the numbers.

The most significant learning experience that I had was getting to understand operationalisation. The area that I found interesting and relevant was social media engagement behaviour, and hence, I decided on that as my research topic. But, after some time, I realised there is more to research than an interesting topic. A researcher needs to convert general concepts into measurable quantities which can be tested statistically. Initially, this was challenging as accuracy and definition were needed. I had to determine the definitions of concepts like “engagement,” “sentiment”, and “post type” in the study and how they could be quantitatively measured through data. This experience was useful in understanding the relationships between theory and measurement in quantitative research.

I also had a big learning curve learning SPSS. The software was at first confusing and difficult. The interface appeared to be technical, and there were numerous tables and values in the statistical outputs which I was unable to fully grasp. I was so overwhelmed with the terms that were used for the first time that I did a One-Way ANOVA test. I felt like I had overcome all of them, including “Between Groups,” “Within

Groups,” “Mean Square,” and “F value.” There was a point in time when the software didn't seem to offer much in the way of help and was more of a challenge.

As I continued to interact with the students, my understanding of the statistical tests grew as I started to understand the underlying logic of the tests. I learned that ANOVA is a test to determine if there are large differences between groups, which are not likely due to random variation. Upon grasping this concept, the output from the statistical analysis of the product became easier to understand. The F statistic was only meaningful because I knew the question being addressed by the statistic. The same is true for the p-value: it was no longer a number, but a tool to consider and determine whether the evidence is sufficiently compelling to conclude.

One of the key learning experiences within the module was to check the assumptions. I performed the Shapiro-Wilk normality test initially and got a significant result, so I thought that I had made a mistake in the analysis. I was wondering if maybe it was all wrong from the beginning. But, being a bit of a bookworm, I read Field (2018) and Pallant (2020), and learned that violations of normality are not so much of an issue when sample sizes are large enough. This was valuable because it was a learning experience on a different way of conducting research beyond just going through the motions. Researchers need to be aware of why they have made their methodological decisions and explain why their decisions were made, in relation to academic literature. This was a really interesting experience, which made me feel as though I was more of an independent researcher instead of a student doing a bunch of statistics exercises.

The result that I got from my study was also interesting because it didn't always go in the direction that I thought it would go. The sentiment was anticipated to have a high positive value with engagement. The results turned out to be somewhat more complicated, however. The extent to which sentiment accounted for the variance in sharing behaviour was not great, and there was a negative correlation between sentiment and sharing. I started out feeling disappointed because I thought that I would have had a more definite and pronounced outcome.

On reflection of more literature, I found that the findings were complex, as was human behaviour in practice. Brady et al. (2017), Berger and Milkman (2012) and Stieglitz and Dang-Xuan (2013) found that emotional content can have opposing impacts on

sharing behaviour in various situations. I found that big and small numbers and statistics were not always as significant as they appeared. The social sciences are an area of study that has many variable factors affecting human behaviour, and even a small R-squared can help to find valuable insight.

The most important takeaway from this module was knowing how crucial honesty is in research. Research is not about looking for results that you want. Rather, it's about correctly reporting the information presented and properly interpreting the information that's presented. This way of thinking has impacted my thinking about academic research and evidence.

This module has also shaped my thoughts on what I would like to do as research when I become a DBA. My research is on Digital business strategy and Organisational behaviour in techno literate contexts. These are the areas where quantitative methods will be helpful, as they will be able to be used to test relationships between variables in larger samples. These skills (such as developing a hypothesis, operationalising variables and interpreting statistics) will be applicable to my future research.

Alongside this, I learned about the limitations of quantitative methods during this module. While relationships and patterns can be identified through statistical analysis, they do not necessarily explain why there are relationships. Numbers are not enough to answer some organisational behavioural questions. As such, I now have a greater understanding of the benefits of qualitative research, including interviews and case studies. I think that in respect of methodology, you have to always rely on the research question!

This module has altered my perceptions about academic research. I now critically assess studies, taking into account, among other things, the size of the samples, assumptions, measurement of the variables and the statistical validity. I question if findings are adequately supported through evidence and if findings may be coincidental. It has been one of the most significant achievements of the module to achieve this perspective.

Conclusion

The purpose of this study was to understand the factors that affect the social media engagement behaviour with the help of the Uses and Gratifications Theory (UGT). A quantitative approach was used to analyse 200 social media posts from Facebook, Instagram and Twitter. The results revealed that the three research objectives were met.

The findings indicated that there is variation in engagement levels in different social media. There was a notable difference in engagement between different platforms, with Instagram and Facebook seeing much more than Twitter. The type of post also makes a big difference in engagement, according to the study. The most engaged content was videos and polls, indicating a preference for interactive and visually appealing content. Lastly, the results indicated that it is sentiment that significantly influences the sharing behavior. There were a higher number of posts with negative sentiment with shared information, which suggests that emotional content can motivate users to share information.

Overall, the findings align with the Uses and Gratifications Theory, indicating that users actively seek out platforms and content that align with their needs and interests. The study also offers valuable information for organisations, digital marketers and social media managers. The selection of the appropriate platform, creation of interesting content and taking into account the emotional aspect of the content can lead to better engagement.

While there are some limitations in this study, it offers valuable insights into the factors affecting social media engagement. Future research could expand upon this work by incorporating more data, such as different social media platforms and other variables that could impact user engagement.

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Appendices

Appendix A: SPSS Output – One-Way ANOVA (Platform and Engagement)

Descriptives

Total Engagement

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Facebook	64	3423.03	1713.654	214.207	2994.97	3851.09	498	6410
Instagram	72	3757.44	1746.264	205.799	3347.09	4167.80	539	6198
Twitter	64	1725.22	1012.067	126.508	1472.41	1978.03	435	4032
Total	200	3000.12	1769.098	125.094	2753.44	3246.80	435	6410

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Total Engagement	Based on Mean	13.401	2	197	<.001
	Based on Median	12.482	2	197	<.001
	Based on Median and with adjusted df	12.482	2	177.549	<.001
	Based on trimmed mean	13.879	2	197	<.001

ANOVA

Total Engagement

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	156765438.5	2	78382719.23	33.133	<.001
Within Groups	466046246.7	197	2365716.988		
Total	622811685.1	199			

Post Hoc Tests

ONEWAY TotalEngagement BY post_type_num

/STATISTICS DESCRIPTIVES HOMOGENEITY

/MISSING ANALYSIS

/CRITERIA=CILEVEL(0.95)

/POSTHOC=TUKEY ALPHA(0.05).

Multiple Comparisons

Dependent Variable: Total Engagement

Tukey HSD

(I) platforms	(J) platforms	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Facebook	Instagram	-334.413	264.238	.416	-958.43	289.60
	Twitter	1697.813 [*]	271.898	<.001	1055.71	2339.92
Instagram	Facebook	334.413	264.238	.416	-289.60	958.43
	Twitter	2032.226 [*]	264.238	<.001	1408.21	2656.24
Twitter	Facebook	-1697.812 [*]	271.898	<.001	-2339.92	-1055.71
	Instagram	-2032.226 [*]	264.238	<.001	-2656.24	-1408.21

*. The mean difference is significant at the 0.05 level.

Total Engagement

Tukey HSD^{a,b}

platforms	N	Subset for alpha = 0.05	
		1	2
Twitter	64	1725.22	
Facebook	64		3423.03
Instagram	72		3757.44
Sig.		1.000	.423

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 66.462.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Appendix B: SPSS Output – One-Way ANOVA (Post Type and Engagement)

Descriptives

Total Engagement

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
1	42	2228.62	1127.440	173.968	1877.28	2579.95	446	4145
2	34	2601.47	1637.973	280.910	2029.95	3172.99	517	5482
3	52	3030.73	1754.177	243.261	2542.36	3519.10	498	6051
4	26	3746.38	1702.912	333.968	3058.56	4434.21	750	6222
5	46	3542.78	2077.656	306.334	2925.79	4159.77	435	6410
Total	200	3000.12	1769.098	125.094	2753.44	3246.80	435	6410

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Total Engagement	Based on Mean	6.466	4	195	<.001
	Based on Median	4.518	4	195	.002
	Based on Median and with adjusted df	4.518	4	172.179	.002
	Based on trimmed mean	6.377	4	195	<.001

ANOVA

Total Engagement

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	58476914.53	4	14619228.63	5.052	<.001
Within Groups	564334770.6	195	2894024.465		
Total	622811685.1	199			

Post Hoc Tests

Multiple Comparisons

Dependent Variable: Total Engagement

Tukey HSD

(I) post_type_num	(J) post_type_num	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1	2	-372.852	392.459	.877	-1453.47	707.77
	3	-802.112	352.930	.158	-1773.89	169.67
	4	-1517.766*	424.516	.004	-2686.66	-348.87
	5	-1314.164*	363.069	.003	-2313.86	-314.46
2	1	372.852	392.459	.877	-707.77	1453.47
	3	-429.260	375.197	.783	-1462.35	603.83
	4	-1144.914	443.201	.077	-2365.25	75.43
	5	-941.312	384.749	.108	-2000.71	118.08
3	1	802.112	352.930	.158	-169.67	1773.89
	2	429.260	375.197	.783	-603.83	1462.35
	4	-715.654	408.611	.405	-1840.75	409.44
	5	-512.052	344.337	.572	-1460.17	436.07
4	1	1517.766*	424.516	.004	348.87	2686.66
	2	1144.914	443.201	.077	-75.43	2365.25
	3	715.654	408.611	.405	-409.44	1840.75
	5	203.602	417.399	.988	-945.70	1352.90
5	1	1314.164*	363.069	.003	314.46	2313.86
	2	941.312	384.749	.108	-118.08	2000.71
	3	512.052	344.337	.572	-436.07	1460.17
	4	-203.602	417.399	.988	-1352.90	945.70

*. The mean difference is significant at the 0.05 level.

Homogeneous Subsets

Total Engagement

Tukey HSD^{a,b}

post_type_num	N	Subset for alpha = 0.05		
		1	2	3
1	42	2228.62		
2	34	2601.47	2601.47	
3	52	3030.73	3030.73	3030.73
5	46		3542.78	3542.78
4	26			3746.38
Sig.		.248	.119	.361

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 37.692.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Appendix C: SPSS Output – Pearson Correlation and Linear Regression (Sentiment and Shares)

Correlations

		sentiment_score_num	shares
sentiment_score_num	Pearson Correlation	1	-.283**
	Sig. (2-tailed)		<.001
	N	200	200
shares	Pearson Correlation	-.283**	1
	Sig. (2-tailed)	<.001	
	N	200	200

** . Correlation is significant at the 0.01 level (2-tailed).

Regression

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	sentiment_score_num ^b	.	Enter

a. Dependent Variable: shares

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.283 ^a	.080	.076	272.256

a. Predictors: (Constant), sentiment_score_num

Appendix D: Dataset Summary

post_id	platform	post_type	post_type_num	post_time	likes	comments	shares	Total Engagement	post_day	sentiment_score	sentiment_score_num
1	Facebook	image	2	17/08/2023 14:45	2121	474	628	3223	Thursday	positive	3

2	Face book	caro usel	3	14/05 /2023 00:45	36 60	432	69 4	4786	Sund ay	neutral	2
3	Insta gra m	poll	4	21/02 /2023 16:15	49 55	408	68 8	6051	Tues day	negativ e	1
4	Twit ter	imag e	2	16/11 /2023 00:45	11 83	90	18 7	1460	Thurs day	negativ e	1
5	Twit ter	vide o	5	23/05 /2023 00:30	34 99	247	28 6	4032	Tues day	positive	3
6	Insta gra m	caro usel	3	05/05 /2023 20:00	25 6	186	21 1	653	Frida y	neutral	2
7	Insta gra m	imag e	2	26/02 /2023 11:45	19 82	30	90 6	2918	Sund ay	positive	3
8	Insta gra m	text	1	28/10 /2023 19:30	12 74	45	21 6	1535	Satur day	neutral	2
9	Face book	vide o	5	02/05 /2023 06:15	31 7	249	22 1	787	Tues day	neutral	2
10	Twit ter	caro usel	3	11/05 /2023 11:00	18 78	225	43 8	2541	Thurs day	neutral	2
11	Twit ter	text	1	08/12 /2023 02:15	14 46	44	52	1542	Frida y	negativ e	1
12	Twit ter	vide o	5	15/06 /2023 03:15	30 4	42	89	435	Thurs day	positive	3
13	Face book	caro usel	3	11/11 /2023 15:45	45	78	37 5	498	Satur day	negativ e	1
14	Twit ter	text	1	30/09 /2023 10:30	13 33	144	12 3	1600	Satur day	positive	3
15	Face book	caro usel	3	09/01 /2023 20:00	88 9	314	26 2	1465	Mon day	positive	3
16	Twit ter	imag e	2	10/02 /2023 13:00	23 48	154	18	2520	Frida y	neutral	2
17	Insta gra m	poll	4	05/07 /2023 05:15	28 72	10	73 6	3618	Wed nesd ay	positive	3
18	Twit ter	text	1	23/07 /2023 05:45	51 2	123	33 8	973	Sund ay	neutral	2

19	Twitter	text	1	20/11/2023 02:00	2013	122	183	2318	Monday	positive	3
20	Facebook	image	2	02/02/2023 16:00	455	86	79	620	Thursday	positive	3
21	Twitter	poll	4	02/05/2023 06:15	559	136	55	750	Tuesday	neutral	2
22	Twitter	carousel	3	30/01/2023 13:30	1961	44	439	2444	Monday	positive	3
23	Twitter	text	1	02/10/2023 12:15	332	109	348	789	Monday	positive	3
24	Instagram	carousel	3	01/01/2023 20:00	5000	80	399	5479	Sunday	positive	3
25	Twitter	poll	4	17/05/2023 00:15	898	130	480	1508	Wednesday	positive	3
26	Facebook	carousel	3	05/10/2023 06:30	1992	70	515	2577	Thursday	negative	1
27	Instagram	text	1	06/10/2023 10:00	3161	162	137	3460	Friday	positive	3
28	Facebook	poll	4	01/03/2023 08:00	2083	500	388	2971	Wednesday	neutral	2
29	Facebook	image	2	07/01/2023 10:30	548	153	731	1432	Saturday	negative	1
30	Facebook	carousel	3	03/02/2023 00:30	4594	216	739	5549	Friday	positive	3
31	Facebook	poll	4	10/09/2023 13:45	4795	449	978	6222	Sunday	negative	1
32	Instagram	image	2	01/07/2023 14:45	4665	202	183	5050	Saturday	positive	3
33	Twitter	video	5	27/09/2023 19:00	119	147	240	506	Wednesday	positive	3
34	Twitter	poll	4	09/02/2023 15:30	2253	162	28	2443	Thursday	positive	3
35	Instagram	image	2	06/06/2023 19:30	1309	201	852	2362	Tuesday	negative	1

36	Face book	video	5	08/04/2023 19:15	5000	500	43	5543	Saturday	positive	3
37	Face book	video	5	11/05/2023 00:30	4245	59	83	4387	Thursday	neutral	2
38	Twitter	poll	4	02/05/2023 00:30	2463	187	445	3095	Tuesday	positive	3
39	Face book	video	5	01/01/2023 06:00	5000	430	980	6410	Sunday	neutral	2
40	Instagram	carousel	3	04/08/2023 12:45	447	333	845	1625	Friday	negative	1
41	Twitter	carousel	3	27/12/2023 11:30	667	176	461	1304	Wednesday	positive	3
42	Instagram	video	5	23/11/2023 02:00	4929	252	730	5911	Thursday	negative	1
43	Twitter	carousel	3	31/03/2023 16:00	2586	97	85	2768	Friday	positive	3
44	Instagram	text	1	06/07/2023 08:00	3259	50	177	3486	Thursday	negative	1
45	Twitter	video	5	01/12/2023 10:00	2236	132	118	2486	Friday	positive	3
46	Instagram	text	1	16/05/2023 22:15	2251	380	427	3058	Tuesday	positive	3
47	Face book	poll	4	08/08/2023 17:45	4726	44	993	5763	Tuesday	negative	1
48	Face book	video	5	22/03/2023 03:15	5000	232	16	5248	Wednesday	negative	1
49	Twitter	image	2	17/04/2023 15:00	725	169	298	1192	Monday	neutral	2
50	Instagram	text	1	12/07/2023 00:00	1551	206	127	1884	Wednesday	negative	1
51	Twitter	text	1	14/02/2023 18:00	1268	73	251	1592	Tuesday	positive	3
52	Twitter	image	2	14/07/2023 15:00	950	113	327	1390	Friday	positive	3

53	Twitter	video	5	12/11/2023 17:30	1498	46	96	1640	Sunday	positive	3
54	Instagram	image	2	21/01/2023 01:00	4297	360	825	5482	Saturday	negative	1
55	Twitter	carousel	3	02/10/2023 23:30	592	34	496	1122	Monday	neutral	2
56	Instagram	image	2	13/03/2023 23:15	3401	190	230	3821	Monday	negative	1
57	Instagram	video	5	13/07/2023 09:15	4846	134	498	5478	Thursday	neutral	2
58	Facebook	video	5	27/12/2023 04:00	2204	116	728	3048	Wednesday	neutral	2
59	Twitter	video	5	24/12/2023 07:45	344	99	194	637	Sunday	neutral	2
60	Instagram	carousel	3	19/05/2023 04:30	4763	332	956	6051	Friday	positive	3
61	Instagram	video	5	31/12/2023 22:30	3544	167	761	4472	Sunday	negative	1
62	Facebook	carousel	3	27/01/2023 15:45	3742	227	849	4818	Friday	negative	1
63	Twitter	image	2	15/05/2023 06:30	227	163	127	517	Monday	neutral	2
64	Instagram	carousel	3	19/04/2023 19:45	130	452	724	1306	Wednesday	neutral	2
65	Instagram	image	2	20/09/2023 06:00	3982	314	326	4622	Wednesday	positive	3
66	Facebook	text	1	03/01/2023 03:00	2265	39	318	2622	Tuesday	positive	3
67	Facebook	carousel	3	23/04/2023 08:15	2026	390	165	2581	Sunday	negative	1
68	Instagram	video	5	28/12/2023 16:45	560	486	677	1723	Thursday	negative	1
69	Twitter	image	2	14/10/2023 18:45	187	89	284	560	Saturday	neutral	2

70	Face book	text	1	12/06 /2023 09:30	30 94	86	96 5	4145	Mon day	negativ e	1
71	Insta gra m	vide o	5	10/04 /2023 00:00	33 98	261	63 0	4289	Mon day	neutral	2
72	Face book	caro usel	3	05/05 /2023 16:45	16 90	257	65 6	2603	Frida y	neutral	2
73	Face book	text	1	18/07 /2023 22:00	30 26	11	76 1	3798	Tues day	positive	3
74	Insta gra m	vide o	5	14/04 /2023 10:30	50 00	454	74 4	6198	Frida y	positive	3
75	Face book	vide o	5	26/07 /2023 20:15	50 00	500	40 4	5904	Wed nesd ay	positive	3
76	Insta gra m	text	1	27/07 /2023 19:15	21 53	81	11 4	2348	Thurs day	neutral	2
77	Twit ter	caro usel	3	05/07 /2023 18:15	35 71	102	96	3769	Wed nesd ay	positive	3
78	Insta gra m	poll	4	19/01 /2023 07:15	29 90	30	36 5	3385	Thurs day	positive	3
79	Insta gra m	caro usel	3	13/12 /2023 04:45	46 78	189	78 5	5652	Wed nesd ay	positive	3
80	Face book	text	1	25/06 /2023 15:15	55 3	320	31 2	1185	Sund ay	positive	3
81	Face book	vide o	5	04/01 /2023 18:30	26 42	33	41 3	3088	Wed nesd ay	neutral	2
82	Insta gra m	caro usel	3	19/11 /2023 12:30	46 56	314	75 7	5727	Sund ay	negativ e	1
83	Insta gra m	vide o	5	06/12 /2023 04:00	50 00	173	79 2	5965	Wed nesd ay	negativ e	1
84	Face book	caro usel	3	03/10 /2023 19:00	12 03	263	41 7	1883	Tues day	negativ e	1
85	Face book	text	1	06/07 /2023 07:00	25 66	368	30 4	3238	Thurs day	neutral	2
86	Twit ter	text	1	25/11 /2023 07:30	24 16	50	62	2528	Satur day	positive	3

87	Instagram	text	1	23/05/2023 22:30	15	70	454	539	Tuesday	neutral	2
88	Facebook	text	1	03/05/2023 12:30	3404	244	67	3715	Wednesday	positive	3
89	Twitter	carousel	3	03/05/2023 08:00	2884	197	339	3420	Wednesday	positive	3
90	Instagram	poll	4	19/03/2023 04:00	3195	109	243	3547	Sunday	negative	1
91	Facebook	carousel	3	15/09/2023 00:45	3956	402	462	4820	Friday	negative	1
92	Facebook	video	5	23/02/2023 17:15	1857	216	344	2417	Thursday	positive	3
93	Instagram	carousel	3	07/05/2023 00:30	951	432	734	2117	Sunday	negative	1
94	Facebook	image	2	27/11/2023 04:30	1694	207	290	2191	Monday	positive	3
95	Instagram	poll	4	07/03/2023 19:15	3005	124	517	3646	Tuesday	positive	3
96	Instagram	carousel	3	12/07/2023 17:45	36	294	911	1241	Wednesday	positive	3
97	Twitter	video	5	27/10/2023 23:45	314	108	458	880	Friday	neutral	2
98	Twitter	text	1	05/08/2023 08:45	229	179	38	446	Saturday	positive	3
99	Instagram	poll	4	29/12/2023 12:15	5000	500	204	5704	Friday	positive	3
100	Instagram	image	2	06/06/2023 21:00	4483	357	25	4865	Tuesday	neutral	2
101	Facebook	image	2	17/08/2023 14:45	2121	474	628	3223	Thursday	positive	3
102	Facebook	carousel	3	14/05/2023 00:45	3660	432	694	4786	Sunday	neutral	2
103	Instagram	poll	4	21/02/2023 16:15	4955	408	688	6051	Tuesday	negative	1

104	Twitter	image	2	16/11/2023 00:45	1183	90	187	1460	Thursday	negative	1
105	Twitter	video	5	23/05/2023 00:30	3499	247	286	4032	Tuesday	positive	3
106	Instagram	carousel	3	05/05/2023 20:00	256	186	211	653	Friday	neutral	2
107	Instagram	image	2	26/02/2023 11:45	1982	30	906	2918	Sunday	positive	3
108	Instagram	text	1	28/10/2023 19:30	1274	45	216	1535	Saturday	neutral	2
109	Facebook	video	5	02/05/2023 06:15	317	249	221	787	Tuesday	neutral	2
110	Twitter	carousel	3	11/05/2023 11:00	1878	225	438	2541	Thursday	neutral	2
111	Twitter	text	1	08/12/2023 02:15	1446	44	52	1542	Friday	negative	1
112	Twitter	video	5	15/06/2023 03:15	304	42	89	435	Thursday	positive	3
113	Facebook	carousel	3	11/11/2023 15:45	45	78	375	498	Saturday	negative	1
114	Twitter	text	1	30/09/2023 10:30	1333	144	123	1600	Saturday	positive	3
115	Facebook	carousel	3	09/01/2023 20:00	889	314	262	1465	Monday	positive	3
116	Twitter	image	2	10/02/2023 13:00	2348	154	18	2520	Friday	neutral	2
117	Instagram	poll	4	05/07/2023 05:15	2872	10	736	3618	Wednesday	positive	3
118	Twitter	text	1	23/07/2023 05:45	512	123	338	973	Sunday	neutral	2
119	Twitter	text	1	20/11/2023 02:00	2013	122	183	2318	Monday	positive	3
120	Facebook	image	2	02/02/2023 16:00	455	86	79	620	Thursday	positive	3

121	Twitter	poll	4	02/05/2023 06:15	559	136	55	750	Tuesday	neutral	2
122	Twitter	carousel	3	30/01/2023 13:30	1961	44	439	2444	Monday	positive	3
123	Twitter	text	1	02/10/2023 12:15	332	109	348	789	Monday	positive	3
124	Instagram	carousel	3	01/01/2023 20:00	5000	80	399	5479	Sunday	positive	3
125	Twitter	poll	4	17/05/2023 00:15	898	130	480	1508	Wednesday	positive	3
126	Facebook	carousel	3	05/10/2023 06:30	1992	70	515	2577	Thursday	negative	1
127	Instagram	text	1	06/10/2023 10:00	3161	162	137	3460	Friday	positive	3
128	Facebook	poll	4	01/03/2023 08:00	2083	500	388	2971	Wednesday	neutral	2
129	Facebook	image	2	07/01/2023 10:30	548	153	731	1432	Saturday	negative	1
130	Facebook	carousel	3	03/02/2023 00:30	4594	216	739	5549	Friday	positive	3
131	Facebook	poll	4	10/09/2023 13:45	4795	449	978	6222	Sunday	negative	1
132	Instagram	image	2	01/07/2023 14:45	4665	202	183	5050	Saturday	positive	3
133	Twitter	video	5	27/09/2023 19:00	119	147	240	506	Wednesday	positive	3
134	Twitter	poll	4	09/02/2023 15:30	2253	162	28	2443	Thursday	positive	3
135	Instagram	image	2	06/06/2023 19:30	1309	201	852	2362	Tuesday	negative	1
136	Facebook	video	5	08/04/2023 19:15	5000	500	43	5543	Saturday	positive	3
137	Facebook	video	5	11/05/2023 00:30	4245	59	83	4387	Thursday	neutral	2

138	Twitter	poll	4	02/05/2023 00:30	2463	187	445	3095	Tuesday	positive	3
139	Facebook	video	5	01/01/2023 06:00	50	430	980	6410	Sunday	neutral	2
140	Instagram	carousel	3	04/08/2023 12:45	447	333	845	1625	Friday	negative	1
141	Twitter	carousel	3	27/12/2023 11:30	667	176	461	1304	Wednesday	positive	3
142	Instagram	video	5	23/11/2023 02:00	4929	252	730	5911	Thursday	negative	1
143	Twitter	carousel	3	31/03/2023 16:00	2586	97	85	2768	Friday	positive	3
144	Instagram	text	1	06/07/2023 08:00	3259	50	177	3486	Thursday	negative	1
145	Twitter	video	5	01/12/2023 10:00	2236	132	118	2486	Friday	positive	3
146	Instagram	text	1	16/05/2023 22:15	2251	380	427	3058	Tuesday	positive	3
147	Facebook	poll	4	08/08/2023 17:45	4726	44	993	5763	Tuesday	negative	1
148	Facebook	video	5	22/03/2023 03:15	50	232	16	5248	Wednesday	negative	1
149	Twitter	image	2	17/04/2023 15:00	725	169	298	1192	Monday	neutral	2
150	Instagram	text	1	12/07/2023 00:00	1551	206	127	1884	Wednesday	negative	1
151	Twitter	text	1	14/02/2023 18:00	1268	73	251	1592	Tuesday	positive	3
152	Twitter	image	2	14/07/2023 15:00	950	113	327	1390	Friday	positive	3
153	Twitter	video	5	12/11/2023 17:30	1498	46	96	1640	Sunday	positive	3
154	Instagram	image	2	21/01/2023 01:00	4297	360	825	5482	Saturday	negative	1

155	Twitter	carousel	3	02/10/2023 23:30	592	34	496	1122	Monday	neutral	2
156	Instagram	image	2	13/03/2023 23:15	3401	190	230	3821	Monday	negative	1
157	Instagram	video	5	13/07/2023 09:15	4846	134	498	5478	Thursday	neutral	2
158	Facebook	video	5	27/12/2023 04:00	2204	116	728	3048	Wednesday	neutral	2
159	Twitter	video	5	24/12/2023 07:45	344	99	194	637	Sunday	neutral	2
160	Instagram	carousel	3	19/05/2023 04:30	4763	332	956	6051	Friday	positive	3
161	Instagram	video	5	31/12/2023 22:30	3544	167	761	4472	Sunday	negative	1
162	Facebook	carousel	3	27/01/2023 15:45	3742	227	849	4818	Friday	negative	1
163	Twitter	image	2	15/05/2023 06:30	227	163	127	517	Monday	neutral	2
164	Instagram	carousel	3	19/04/2023 19:45	130	452	724	1306	Wednesday	neutral	2
165	Instagram	image	2	20/09/2023 06:00	3982	314	326	4622	Wednesday	positive	3
166	Facebook	text	1	03/01/2023 03:00	2265	39	318	2622	Tuesday	positive	3
167	Facebook	carousel	3	23/04/2023 08:15	2026	390	165	2581	Sunday	negative	1
168	Instagram	video	5	28/12/2023 16:45	560	486	677	1723	Thursday	negative	1
169	Twitter	image	2	14/10/2023 18:45	187	89	284	560	Saturday	neutral	2
170	Facebook	text	1	12/06/2023 09:30	3094	86	965	4145	Monday	negative	1
171	Instagram	video	5	10/04/2023 00:00	3398	261	630	4289	Monday	neutral	2

172	Face book	caro usel	3	05/05 /2023 16:45	16 90	257	65 6	2603	Frida y	neutral	2
173	Face book	text	1	18/07 /2023 22:00	30 26	11	76 1	3798	Tues day	positive	3
174	Insta gra m	vide o	5	14/04 /2023 10:30	50 00	454	74 4	6198	Frida y	positive	3
175	Face book	vide o	5	26/07 /2023 20:15	50 00	500	40 4	5904	Wed nesd ay	positive	3
176	Insta gra m	text	1	27/07 /2023 19:15	21 53	81	11 4	2348	Thurs day	neutral	2
177	Twit ter	caro usel	3	05/07 /2023 18:15	35 71	102	96	3769	Wed nesd ay	positive	3
178	Insta gra m	poll	4	19/01 /2023 07:15	29 90	30	36 5	3385	Thurs day	positive	3
179	Insta gra m	caro usel	3	13/12 /2023 04:45	46 78	189	78 5	5652	Wed nesd ay	positive	3
180	Face book	text	1	25/06 /2023 15:15	55 3	320	31 2	1185	Sund ay	positive	3
181	Face book	vide o	5	04/01 /2023 18:30	26 42	33	41 3	3088	Wed nesd ay	neutral	2
182	Insta gra m	caro usel	3	19/11 /2023 12:30	46 56	314	75 7	5727	Sund ay	negativ e	1
183	Insta gra m	vide o	5	06/12 /2023 04:00	50 00	173	79 2	5965	Wed nesd ay	negativ e	1
184	Face book	caro usel	3	03/10 /2023 19:00	12 03	263	41 7	1883	Tues day	negativ e	1
185	Face book	text	1	06/07 /2023 07:00	25 66	368	30 4	3238	Thurs day	neutral	2
186	Twit ter	text	1	25/11 /2023 07:30	24 16	50	62	2528	Satur day	positive	3
187	Insta gra m	text	1	23/05 /2023 22:30	15	70	45 4	539	Tues day	neutral	2
188	Face book	text	1	03/05 /2023 12:30	34 04	244	67	3715	Wed nesd ay	positive	3

189	Twitter	carousel	3	03/05/2023 08:00	2884	197	339	3420	Wednesday	positive	3
190	Instagram	poll	4	19/03/2023 04:00	3195	109	243	3547	Sunday	negative	1
191	Facebook	carousel	3	15/09/2023 00:45	3956	402	462	4820	Friday	negative	1
192	Facebook	video	5	23/02/2023 17:15	1857	216	344	2417	Thursday	positive	3
193	Instagram	carousel	3	07/05/2023 00:30	951	432	734	2117	Sunday	negative	1
194	Facebook	image	2	27/11/2023 04:30	1694	207	290	2191	Monday	positive	3
195	Instagram	poll	4	07/03/2023 19:15	3005	124	517	3646	Tuesday	positive	3
196	Instagram	carousel	3	12/07/2023 17:45	36	294	911	1241	Wednesday	positive	3
197	Twitter	video	5	27/10/2023 23:45	314	108	458	880	Friday	neutral	2
198	Twitter	text	1	05/08/2023 08:45	229	179	38	446	Saturday	positive	3
199	Instagram	poll	4	29/12/2023 12:15	5000	500	204	5704	Friday	positive	3
200	Instagram	image	2	06/06/2023 21:00	4483	357	25	4865	Tuesday	neutral	2