

Impact of Content Optimization on Social Media Engagement: A Data-Backed Analysis of Instagram Content Performance

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DOI: 10.46609/IJSSER.2026.v11i10.035 URL: <https://doi.org/10.46609/IJSSER.2026.v11i10.035>

Received: 9 October 2026 / Accepted: 18 October 2026 / Published: 22 October 2026

1. Introduction

Social media has fundamentally changed the way people consume information, discover ideas and interact with businesses. What once required separate platforms for entertainment, news, communication and shopping can now happen through a single smartphone. Instagram is a particularly strong example of this shift. It has developed from a photo-sharing application into a major environment for entertainment, discovery, creator culture and brand communication, where a product demonstration, a creator's review, a news update and a viral reel can compete for attention within the same feed. For businesses and content creators, this has created an enormous opportunity to reach audiences directly. It has also created a much more difficult question: **how does content stand out when almost everyone is producing it?**

The barriers to creating and publishing content have never been lower. A creator can record, edit and distribute a video using nothing more than a smartphone, while brands can publish content to millions of potential customers without relying exclusively on traditional advertising. The rise of creator-led businesses illustrates how significant this transformation has become. At the same time, the growth of content has made audience attention increasingly competitive. On Instagram, publishing consistently does not necessarily translate into growth or engagement. **HubSpot's 2026 Instagram Marketing Report**, based on a survey of more than 600 global Instagram marketers and data from over 110 million Instagram posts, found that 53% of marketers consider follower growth their biggest challenge, while 32% struggle to generate consistent likes, comments and shares.

This tension between **more content and harder-to-capture attention** has made content optimization increasingly important. Marketers now make deliberate decisions about the format of a post, when it should be published, how frequently an account should post, how much information a caption should contain, which hashtags should be used and whether a post should actively encourage audience interaction. These decisions are particularly relevant because

engagement provides a measurable indication of how audiences respond to content. Likes, comments, shares and saves can signal that users have moved beyond passive exposure and interacted with what a brand or creator has published.

Industry behaviour reflects this growing focus on optimization. [HubSpot's](#) research reports that reels currently generate the highest reported reach, impressions, likes and shares among the formats examined, while direct audience interaction - such as responding to comments and creating interactive content - is identified by 40% of surveyed marketers as the Instagram strategy generating the highest return on investment. At the same time, marketers continue to use a mixture of image posts, videos and reels rather than abandoning static content altogether. These findings illustrate an important reality: there is no single content decision that exists independently of the broader strategy. A brand such as [Duolingo](#), for example, has built a distinctive social presence through humorous, highly recognizable short-form content rather than relying on conventional product advertising. Similarly, brands such as [Nike](#) use a combination of visually distinctive campaigns, athlete-led storytelling and product-focused content to create different forms of audience response. The strategic question is therefore not simply whether a brand should "post more," but what characteristics make its content more likely to generate engagement.

However, popular marketing advice does not always translate into universal rules. Academic research has found that relationships between content characteristics and engagement can vary considerably across platforms, audiences and contexts. A review of 45 studies by [Schreiner, Fischer and Riedl](#) found diverse and sometimes inconclusive evidence concerning the effects of content characteristics on behavioural engagement, highlighting the potential influence of contextual and confounding factors. More recent Instagram research similarly demonstrates that content characteristics can have different effects depending on the context. For example, [Wahid and Gunarto's](#) analysis of 486 Instagram posts from 19 universities found that carousel formats and certain informational characteristics were associated with higher levels of engagement, while promotional and some rational content characteristics produced weaker outcomes.

This inconsistency creates a research opportunity. Much of the existing discussion around Instagram optimization focuses on individual practices - such as choosing the right format or posting at the right time - while social media performance is inherently multidimensional. The present study therefore examines several content optimization factors simultaneously using a large secondary dataset of Instagram posts obtained from Kaggle. The analysis considers **media type, posting time, posting frequency, caption length, hashtag usage and call-to-action presence** in relation to engagement rate, while also examining factors including follower count, account type, content category and day of the week.

The study is guided by the following research question:

To what extent are content optimization factors - including media type, posting time, posting frequency, caption length, hashtag usage and call-to-action presence - associated with Instagram engagement performance?

By combining descriptive statistics, correlation analysis, ANOVA and multiple regression, this research seeks to distinguish between widely held assumptions about social media optimization and relationships supported by empirical evidence. The study does not assume that a particular content format or strategy automatically produces higher engagement; rather, it examines the strength and significance of these relationships within the dataset. In doing so, it aims to contribute both to academic understanding of Instagram engagement and to the practical decisions faced by marketers and content creators operating in an increasingly crowded digital environment.

It is important to note the scope of these findings from the outset. This study examines whether optimization factors are associated with Instagram engagement within a specific dataset of 20 accounts over a one-year period (November 2024–November 2025). The findings cannot be generalized to all Instagram accounts, account types or audience compositions. Results are specific to this dataset and observation period, during which Instagram's algorithm may have remained relatively stable. Readers should therefore interpret the findings as account-specific patterns rather than as universal Instagram principles.

2. Review of Literature

2.1 Social Media Engagement: Definition and Importance

Social media engagement represents the observable ways in which users respond to content published on digital platforms. Unlike simple exposure to a post, engagement reflects an active behavioural response, including actions such as likes, comments, shares and other forms of interaction. Schreiner, Fischer and Riedl (2021) conceptualize content engagement as the measurable result of an individual's interaction with social media content, emphasizing behavioural outcomes because they provide a practical way for organizations to evaluate the performance of their social media activities. Their review of 45 studies demonstrates that engagement has become an important outcome in social media research, while also showing that the relationship between content characteristics and engagement is far from consistent.

Engagement is important to marketers because it provides a measurable indication of audience response. A post that receives likes, comments or shares has generated a different level of audience participation from content that is simply displayed to users. However, engagement

should not be treated as a single, uniform behaviour. A like requires relatively little effort, whereas commenting or sharing can represent a stronger form of participation. Research on social media engagement therefore increasingly distinguishes between different forms and levels of behavioural engagement rather than treating all interactions as equivalent. For example, research by [Tafesse \(2018\)](#) and colleagues has examined engagement as a multidimensional outcome, while empirical work on Instagram has commonly used likes and comments as observable indicators of audience response.

The importance of engagement is also connected to the algorithmic nature of contemporary social media platforms. Users do not encounter every piece of content produced by the accounts they follow; instead, platform ranking systems determine how and where content is surfaced. [Meta](#) has explained that its ranking systems use multiple signals and predictions to determine which content is most relevant to individual users, with engagement-related actions such as likes, comments and shares forming part of the information that can contribute to these predictions. However, Meta also emphasizes that no single signal provides a complete measure of content value and that ranking systems incorporate a wider range of behavioural and contextual information.

This makes the relationship between engagement and visibility more complex than the assumption that higher engagement automatically produces greater reach. Engagement can be one signal within a broader ranking process, but platform distribution is influenced by multiple factors and the systems used to rank content continue to evolve. This complexity makes engagement particularly suitable for empirical analysis. Rather than assuming that a specific type of post will perform better, researchers can examine whether measurable characteristics of content are statistically associated with differences in engagement. Schreiner, Fischer and Riedl's review of 45 studies similarly found that evidence concerning the relationship between content characteristics and behavioural engagement remains diverse and often context-dependent, highlighting the importance of examining these relationships empirically rather than relying on universal content recommendations.

2.2 Content Optimization and Engagement

Content optimization refers broadly to the deliberate adjustment of content characteristics and publication practices with the objective of improving audience response. In an Instagram context, this can include decisions concerning content format, publication timing, posting frequency, caption characteristics, hashtags and interactive elements such as calls to action. These characteristics correspond closely with the dimensions identified in previous social media research. Schreiner et al. (2021), for example, classify content characteristics into categories including topic, media components, length and interactivity. Their review found that media

richness, such as the inclusion of visual components, can be associated with stronger engagement, but also emphasizes that findings are frequently context-dependent and sometimes contradictory.

Content format

Instagram's development from a primarily image-based platform into a video-oriented environment has increased interest in whether different media formats generate different levels of engagement. Industry research currently places considerable emphasis on short-form video. HubSpot's 2026 Instagram Marketing Report, based on responses from more than 600 marketers and analysis of over 110 million Instagram posts, reports that reels generate the highest reported reach, impressions, likes and shares among the formats examined. However, industry performance data should not automatically be interpreted as evidence that reels are universally superior.

Academic evidence illustrates why this distinction matters. Wahid and Gunarto (2021), analysing 486 Instagram posts from 19 Indonesian universities, found that carousel posts were associated with increased likes, while content characteristics such as informational material and the use of questions also influenced engagement. Their findings suggest that the relationship between format and engagement depends partly on the type and purpose of the content rather than on format alone.

Posting frequency and consistency

Posting frequency is another widely discussed component of social media strategy. Marketers frequently recommend maintaining a consistent publishing schedule, based on the assumption that regular content provides more opportunities for audience interaction. However, the academic evidence has historically been less developed than industry advice suggests. Recent research by Tafesse and Hussain (2026), using a panel dataset of 460 Instagram content creators, found a positive relationship between posting consistency and follower engagement, while also demonstrating that this relationship can depend on factors such as competition and follower size.

Other recent research demonstrates why frequency should be examined alongside other content characteristics. Drivas and Vraimaki's (2024) analysis of 1,681 posts from 120 academic-library Instagram accounts examined posting frequency together with caption length, hashtags, emojis and post types. Their findings showed substantial differences in interaction rates between content categories, while the structural characteristics of posts had relatively limited influence. This reinforces the argument that posting more frequently should not automatically be equated with higher engagement.

Posting time

The timing of content publication represents another commonly recommended optimization practice. The underlying logic is straightforward: publishing when an audience is more likely to be active may increase the opportunity for early interaction. However, existing research suggests that the relationship between posting time and engagement is not necessarily universal. Research examining Instagram content has found differences in engagement associated with posting periods, while also demonstrating that the effect can vary according to the account and context being studied.

More broadly, research examining the causal effect of social-media posting time has shown that estimated optimal publication times can differ according to both the type of content and the day on which it is published. This suggests that there is unlikely to be a single posting window that consistently maximizes performance across all content. Industry-level evidence points in a similar direction: HubSpot's Instagram analysis reports meaningful differences in engagement across posting hours while emphasizing that the most effective time is not identical for every account.

Consequently, posting time is better treated as an empirical variable than as a fixed marketing rule. This study therefore considers posting hour as a measurable characteristic and tests its statistical association with engagement rather than assuming in advance that morning, afternoon or evening publication will produce superior engagement.

Captions, hashtags and interactivity

Textual and interactive elements may also influence how audiences respond to social media content. Caption length can affect the amount of information available to users, while hashtags can facilitate content discovery by connecting posts with topics or communities. Research examining Instagram hashtags found that hashtag characteristics can influence reach, targeting and engagement, suggesting that the value of hashtags may depend on their relevance and characteristics rather than simply their quantity.

Interactivity represents another potentially important dimension. Calls to action, questions and requests for audience responses can encourage users to move from passive consumption toward active participation. Wahid and Gunarto (2021), for example, found that embedding questions within Instagram posts could enhance likes and comments. This supports the broader argument that content designed to stimulate a response may perform differently from content that communicates information without explicitly inviting interaction.

2.3 Theoretical Framework

Three complementary perspectives provide a useful framework for understanding these relationships.

First, **algorithmic visibility** suggests that engagement occurs within a platform environment where content distribution is mediated by algorithmic systems. Consequently, content characteristics may influence not only direct audience response but potentially the subsequent visibility of a post.

Second, **content–audience fit** suggests that the effectiveness of a content characteristic depends on whether it is appropriate for the audience and communication context. A reel, long caption or large number of hashtags cannot be assumed to generate the same response across different account types or content categories. This perspective helps explain why previous studies have produced inconsistent results.

Third, **network and interactive effects** recognize that social media engagement is inherently relational. Likes, comments and shares can increase the visibility of content to other users, while interactive posts can encourage further participation. Engagement therefore represents not simply an individual response to content but part of a broader process involving creators, audiences and platform-mediated distribution.

2.4 Statistical Approaches to Social Media Engagement

Because engagement can be influenced by several variables simultaneously, quantitative methods are particularly useful for evaluating content optimization. **Correlation analysis** can identify the direction and strength of associations between continuous variables such as caption length, hashtag count, posting frequency and engagement rate. **Analysis of variance (ANOVA)** is appropriate when comparing mean engagement across categorical groups, such as different media formats or time-of-day categories. **Multiple regression analysis** can then assess the combined relationship between several content characteristics and engagement while accounting for relevant control variables.

This integrated approach is preferable to relying on a single statistical comparison. It allows the study to distinguish between variables that may appear associated with engagement independently and those that retain explanatory value when other factors are considered. Recent Instagram research demonstrates the usefulness of this approach: studies have employed correlation, regression and comparative statistical methods to examine relationships between posting practices, follower characteristics and engagement.

2.5 Research Gap

Despite the expanding body of research on social media engagement, important gaps remain. Schreiner et al. (2021) found that evidence concerning the effects of content characteristics on engagement remains diverse and inconclusive, with potential confounding factors contributing to contradictory findings. More recent Instagram research continues to identify inconsistent relationships between content structure and engagement, suggesting that generalized recommendations should be treated cautiously.

A further limitation is that individual studies often concentrate on particular content characteristics, account types or specific contexts. For example, one study may examine hashtags, another content format and another posting consistency. While these studies provide valuable insights, they do not necessarily establish how multiple optimization characteristics perform when considered simultaneously.

The present study addresses this gap by examining **media type, posting time, posting frequency, caption length, hashtag usage and call-to-action presence within a single empirical framework**, while also examining for follower count, account type, content category and day of the week. Using a large secondary dataset of Instagram posts, the study combines descriptive analysis, correlation, ANOVA and regression to assess whether commonly discussed content optimization practices are supported by measurable relationships with engagement. Rather than assuming that optimization produces universally positive outcomes, the research tests these assumptions empirically and considers both significant and non-significant findings.

3. Methodology

This section describes the research design, data source, variables examined, data preparation procedures, and statistical techniques employed to investigate the relationship between Instagram content optimization and audience engagement. The methodology was designed to examine commonly discussed content optimization practices empirically rather than assume that any individual practice universally improves performance.

3.1 Research Design

This study adopts a **quantitative, observational research design** based on secondary data. Rather than manipulating content characteristics experimentally, the research examines naturally occurring Instagram posts and evaluates the extent to which different characteristics of those posts are associated with variations in engagement performance.

The study uses a large secondary dataset of Instagram posts obtained from **Kaggle**, containing post-level information across multiple Instagram accounts. This approach allows content characteristics and engagement outcomes to be examined across a substantially larger number of observations than would be practical through primary data collection alone.

The research examines whether commonly discussed content optimization factors are associated with Instagram engagement performance. Specifically, the study evaluates:

1. Whether engagement varies across different media types and content categories.
2. Whether posting time and posting frequency are associated with engagement.
3. Whether caption length and hashtag usage are related to engagement.
4. Whether the presence of a call to action is associated with differences in engagement.
5. Whether these relationships remain meaningful when multiple content and account characteristics are considered simultaneously.
6. Whether engagement differs across days of the week and broad periods of the day.

The research is guided by the question:

To what extent are content optimization factors—including media type, posting time, posting frequency, caption length, hashtag usage and call-to-action presence—associated with Instagram engagement performance?

The observational design is important because the study aims to evaluate patterns within naturally occurring social media data rather than experimentally manipulate individual content characteristics. Accordingly, the analysis identifies statistical associations rather than establishing causal effects.

3.2 Data Source and Sample

The study uses a secondary dataset of Instagram posts obtained from **Kaggle**. The original dataset contained **30,999 rows**, of which **29,999 observations contained valid post-level data** used for statistical analysis. The remaining 1,000 rows were blank or missing observations and were not treated as substantive posts.

The valid dataset represents posts from **20 Instagram accounts**, identified through the `account_id` variable. The number of observations contributed by each account varies between approximately 1,400 and 1,600 posts. The frequency distribution therefore indicates a relatively

balanced contribution across the accounts, while also demonstrating that the dataset contains repeated observations from the same accounts. The account frequencies range from 1,392 posts to 1,599 posts.

The observation period extends from **19 November 2024 to 19 November 2025**, based on the **post_date** variable. The dataset contains information relating to individual posts, including account characteristics, content characteristics, publication information and engagement outcomes.

The use of multiple accounts is important to the research design because content performance can differ according to account characteristics and audience context. At the same time, because the dataset contains multiple observations from the same 20 accounts, the findings should not be interpreted as if all 29,999 observations represented completely independent accounts.

As a result, the findings reported in this study apply specifically to these 20 accounts and this observation period, and should not be interpreted as representative of Instagram accounts or engagement patterns more broadly.

3.3 Variables and Operationalisation

The analysis focuses on **engagement rate as the principal outcome variable**, with content, publishing and account characteristics examined as explanatory variables.

3.3.1 Dependent Variable

The dependent variable in the analysis is engagement rate (**engagement_rate**), operationalised as the proportion of a post's audience interactions (likes, comments, shares and saves) relative to the post's reach. Engagement rate therefore represents the level of audience interaction generated by a post relative to its exposure and provides the principal measure of post performance in the study.

The use of engagement rate is consistent with the study's focus on measurable behavioural responses to social media content. Engagement is treated as an observable indication of audience response rather than as a single uniform behaviour, since different forms of interaction can represent different levels of participation. The original dataset contained 30,999 rows, of which 1,000 were blank or missing data. These were removed, leaving 29,999 observations. The dataset was obtained from Kaggle and treated as provided without independent validation of data accuracy.

Important note: Engagement rate, calculated as interactions/reach, combines two distinct dimensions: (1) audience response to content when exposed (measured by interactions), and (2)

algorithmic distribution of content (measured by reach). Since reach is partly algorithm-determined and may not show content quality alone, engagement rate may reflect platform distribution patterns as much as content characteristics. This conflation limits interpretation of which content features actually influence audience response.

3.3.2 Content and Publishing Variables

The principal content optimisation variables are:

- **Media type** (`media_type`): identifies the format of the post, with the dataset containing image, carousel and reel posts.
- **Content category** (`content_category`): identifies the thematic category of the post, including categories such as Beauty, Comedy, Fashion, Fitness, Food, Lifestyle, Music, Photography, Technology and Travel.
- **Posting hour** (`post_hour`): records the hour at which the post was published, ranging from 0 to 23.
- **Posting frequency** (`post_frequency`): represents the total number of posts contributed by an account during the observation period. This is an account-level measure (constant for all posts from the same account) rather than a post-level optimization variable. It measures differences between high-posting and low-posting accounts but cannot directly assess whether increasing posting frequency for an individual account affects engagement.
- **Caption length** (`caption_length`): measures the length of the caption associated with each post.
- **Hashtag count** (`hashtags_count`): records the number of hashtags used in a post.
- **Call-to-action presence** (`has_call_to_action`): indicates whether a post contains an explicit call to action.

These variables correspond to the content optimization dimensions identified in the research question and literature review. Content optimization in this study is therefore treated as a multidimensional concept encompassing format, timing, frequency, textual characteristics, discoverability and interactivity.

It should be noted that these variables capture structural or quantitative characteristics of a post rather than its creative or perceived quality; measures such as caption length and hashtag count

treat all captions and hashtags as equivalent regardless of their relevance, tone or execution. Quality-based measures — for example, caption clarity, hashtag relevance or visual production quality — could potentially capture these constructs more precisely, but such measures were not available in the dataset and are noted here as a direction for future research.

3.3.3 Temporal Variables

Two additional temporal variables were derived from the publication information.

Day of week (*day_of_week*) was derived from the post date and classified into the seven calendar days: Monday, Tuesday, Wednesday, Thursday, Friday, Saturday and Sunday. This variable was used to examine whether mean engagement differed according to the day on which content was published.

Time of day (*time_of_day*) was derived from *post_hour* and divided into four six-hour periods:

- **Night:** 00:00–05:59
- **Morning:** 06:00–11:59
- **Afternoon:** 12:00–17:59
- **Evening:** 18:00–23:59

This categorisation was introduced as a supplementary analysis to examine whether broad publication periods were associated with differences in engagement, while retaining *post_hour* as a continuous variable for the primary correlation analysis.

This distinction allows the study to examine posting time at two levels: the continuous posting hour and broader time-of-day categories. The latter is therefore used for group comparison rather than as a replacement for the original posting-hour measure.

3.3.4 Account and Contextual Variables

The analysis also considers characteristics that may contribute to differences in engagement between posts. These include:

- **Follower count** (*follower_count*);
- **Account type** (*account_type*); and
- **Traffic source** (*traffic_source*).

Follower count represents the audience size associated with the account, while account type distinguishes between creator and brand accounts. Traffic source identifies how content was surfaced to users, including sources such as Home Feed, Explore, Profile, Hashtags, reels Feed and External. Reach (reach) records the number of unique accounts that viewed a post, while impressions (impressions) record the total number of times a post was displayed, including repeat views by the same account. Followers gained (followers_gained) records the number of new followers attributed to an account following a given post.

These variables are incorporated because engagement does not occur independently of the account and audience context in which content is published. The research framework therefore avoids assuming that a particular format, posting time or caption characteristic will produce the same outcome across all accounts.

3.4 Data Preparation and Quality Checks

Before conducting statistical analysis, the dataset was reviewed to assess the structure and completeness of the available observations. Variables were classified according to their measurement characteristics, with numerical variables treated as continuous measures and categorical variables treated as categorical measures.

Post-level information was retained at the individual observation level so that differences in engagement could be examined across content characteristics. Date and time information were used to derive publication-related measures, including posting hour, day of week and time of day. Account identifiers were used to distinguish observations across the 20 accounts and to calculate the account-level posting-frequency measure.

The dataset contained **1,000 blank or missing rows**, while **29,999 observations** constituted the valid analysis sample. The valid observations contained complete values for the principal variables used in the analysis. Frequency distributions were examined for categorical variables, while descriptive statistics were used to review the range and variability of numerical variables.

The account identifier was also examined to establish the distribution of observations across accounts. The resulting frequencies showed that individual accounts contributed between 1,392 and 1,599 observations. This check was important because the dataset contains repeated post-level observations from the same accounts.

Additional diagnostic checks were conducted before inferential analysis. For regression, collinearity statistics, Q-Q plots of residuals and residual plots were examined. For group comparisons using ANOVA, homogeneity of variance was assessed using Levene's test. These

checks were used to inform the interpretation of the statistical results rather than to assume that all model assumptions were automatically satisfied.

All analyses were conducted using **Jamovi**.

3.5 Data Analysis

All statistical analyses were conducted using Jamovi. The analysis followed a sequential approach beginning with descriptive statistics and progressing to correlation analysis, group comparisons and multiple regression. Each technique served a distinct purpose within the research framework.

Descriptive statistics were first used to establish the overall characteristics and distribution of the dataset. Correlation analysis was then used to examine whether continuous content and account characteristics were linearly associated with engagement rate. ANOVA was used to determine whether engagement differed significantly between categories of selected content and contextual variables, while independent-samples comparisons were used where the explanatory variable contained two groups. Finally, multiple linear regression was used to examine the combined relationship between several explanatory variables and engagement rate.

This sequence allows the analysis to move from describing the observed data to testing individual associations and group differences, before examining whether relationships remain meaningful when multiple characteristics are considered simultaneously. The approach therefore directly supports the central objective of the study: to distinguish between commonly held assumptions about social media optimization and relationships supported by measurable evidence.

3.5.1 Descriptive Statistics

Descriptive statistics were used to summarise the distribution of the principal numerical variables. Measures of **mean, median, standard deviation, minimum and maximum** were examined where appropriate.

Frequency distributions were also generated for categorical variables to establish the composition of the dataset across account type, media type, content category, traffic source, call-to-action presence, day of week and time of day.

These analyses provided an initial description of the sample and established the basis for subsequent statistical comparisons.

3.5.2 Correlation Analysis

Pearson's correlation coefficient was used to examine the direction and strength of linear associations between continuous variables.

The analysis considered relationships involving engagement rate and numerical characteristics including **posting frequency, posting hour, caption length, hashtag count, follower count, reach and followers gained**.

Posting hour was retained as a continuous numerical variable rather than being divided in advance into broad categories for the primary correlation analysis. This approach allows the data to determine whether a systematic linear association exists without imposing an assumed optimal time period in advance.

Posting frequency was treated differently from the purely post-level variables because it is an account-level measure. It represents the total number of posts contributed by an account during the observation period and therefore takes the same value for posts belonging to the same account. Its association with post-level engagement rate is consequently interpreted with caution because the effective variation in this measure is determined by the 20 accounts rather than the full number of posts.

Correlation analysis was selected because it identifies the direction and strength of measurable associations without implying causality.

3.5.3 Analysis of Variance

One-way **Analysis of Variance (ANOVA)** was used to examine whether mean engagement rates differed significantly between groups defined by categorical variables.

ANOVA was conducted for:

- media type;
- content category;
- day of week; and
- time of day.

For each analysis, the null hypothesis was that the mean engagement rate was equal across the relevant groups. The alternative hypothesis was that at least one group mean differed from another.

The assumption of homogeneity of variances was assessed using **Levene's test** before interpreting the ANOVA results. Tukey post-hoc comparisons were computed for each ANOVA to examine pairwise group differences, with these comparisons interpreted with particular caution where the overall ANOVA result was not statistically significant.

The analysis focused on the overall F-statistic, p-value, group means and post-hoc comparisons. This distinction is important because an observed difference in group means does not necessarily indicate a statistically meaningful difference.

3.5.4 Independent-Samples Comparison

Variables containing categorical groups, including account type, media type, content category, traffic source and call-to-action presence, were incorporated into the multiple regression model using reference categories. This allowed the estimated coefficients to represent differences in engagement rate relative to the selected reference category.

3.5.5 Multiple Regression Analysis

A **multiple linear regression model** was used to examine the combined relationship between content optimization characteristics and engagement rate.

Regression analysis allows several explanatory variables to be considered simultaneously and therefore provides a stronger basis for evaluating whether an individual content characteristic retains an association with engagement after accounting for other measurable characteristics.

The regression model included variables relating to post frequency, follower count, followers gained, posting hour, hashtag count, caption length, account type, media type, content category, traffic source and call-to-action presence. Reach was excluded from the regression model despite being available in the dataset, because engagement rate is operationalised relative to reach, meaning the two variables are not conceptually independent; including reach as a predictor would introduce circularity between an explanatory variable and the outcome it is used to construct.

Categorical variables were incorporated into the regression model using reference categories, allowing the estimated coefficients to represent differences relative to the selected reference group. Model performance was assessed using measures of model fit, while individual predictors were evaluated using estimated coefficients, standard errors, test statistics, p-values and confidence intervals.

Collinearity statistics were examined to determine whether strong linear relationships existed among the predictors. Residual plots and Q-Q plots were also examined as part of the regression diagnostics.

The regression analysis should be interpreted as an assessment of **statistical association rather than causal impact**, consistent with the observational design of the study.

The inclusion of followers gained still requires cautious interpretation because it represents a post-performance characteristic rather than a purely exogenous content characteristic. It is therefore treated as an observed contextual variable rather than a definitive causal control. The regression results should consequently be interpreted as an exploratory assessment of statistical association rather than as evidence of independent causal effects.

3.6 Statistical Significance

Statistical significance was assessed using an **alpha level of 0.05**. Results with $p < .05$ were considered statistically significant.

Where available, **95% confidence intervals** were considered alongside p-values to assess the precision of estimated relationships.

The analysis does not interpret statistical significance alone as evidence that a content optimization practice is practically important. This distinction is particularly relevant given the relatively large number of observations in the dataset, as large samples can produce statistically detectable differences even when the magnitude of an association is small.

Accordingly, interpretation of the results considers the direction and magnitude of observed relationships alongside their statistical significance. The study also distinguishes between descriptive differences in group means and differences that are statistically supported.

3.7 Methodological Limitations

The methodology has several limitations that should be considered when interpreting the findings.

1. The study relies on a secondary dataset rather than primary data collected specifically for the research question. Consequently, the analysis is restricted to the variables available in the dataset and cannot account for every factor that may influence Instagram engagement.
2. The observational design identifies associations rather than causal relationships. A statistically significant relationship between a content characteristic and engagement would not establish that changing that characteristic directly causes engagement to increase.

3. Although the dataset contains 29,999 post-level observations, these observations originate from only 20 Instagram accounts. Multiple posts from the same account may share audience characteristics, account history and content strategies. The effective diversity of the sample is therefore considerably smaller than the number of observations suggests. This restricts the generalisability of the findings and means that the results should not be treated as representative of Instagram accounts more broadly.

4. Posting frequency was operationalised as the total number of posts contributed by each account during the observation period. Since the same frequency value is assigned to every post belonging to an account, it is not fully independent at the post level. The analysis therefore captures differences between accounts with varying posting volumes rather than estimating what occurs when a single account changes its posting frequency.

5. The dataset does not measure several plausible determinants of engagement, including visual and creative quality, caption relevance, audience composition, account age, individual post topic and the strength of the relationship between an account and its followers. Their omission places a substantial constraint on the analysis. The null findings should therefore be interpreted as evidence that the quantifiable variables included in the dataset explain little variation in engagement. They do not establish that content optimisation is unimportant overall.

6. The observation period covers only 13 months, from November 2024 to November 2025. This timeframe may be insufficient to capture longer-term seasonal patterns or account development. Instagram's features, recommendation systems and content-distribution mechanisms also change over time. Relationships observed during this period may therefore differ under another version of the service or across a longer period.

7. The regression diagnostics indicated departures from normality and constant variance. Since these conditions affect the reliability of ordinary least-squares standard errors, confidence intervals and significance tests, the regression findings require caution. A model designed for bounded and skewed proportional outcomes would provide a more suitable basis for further analysis.

Given these limitations and the inconsistent findings reported in previous research, the results should be interpreted as evidence of relationships within these 20 accounts and this observation period, rather than as universal rules governing Instagram content strategy.

4. Findings and Results

This section presents the empirical findings of the study based on the analysis of the Instagram dataset. The results are presented in a structured manner, beginning with descriptive statistics to

establish the characteristics and distribution of the observations, followed by an examination of engagement across different content types, posting frequency, and posting time. Statistical tests are then used to assess whether observed differences and relationships are statistically significant. Correlation and regression analyses are used to examine the relationships between engagement and selected content characteristics and to identify variables associated with engagement outcomes. The results are reported objectively using descriptive measures, statistical significance values, effect estimates, and visual representations where appropriate.

4.1 Descriptive Statistics

Descriptive statistics were used to summarise the principal numerical variables included in the dataset and to establish the overall distribution of the observations before conducting further statistical analysis. The analysis reports the sample size, mean, median, standard deviation, minimum, and maximum values for variables related to account characteristics, content characteristics, posting behaviour, and performance outcomes.

Table 4.1
Descriptive Statistics of Study Variables

Variable	N	Mean	Median	SD	Min	Max
Follower count	29,999	10,278	9,044	6,692	3,083	31,095
Reach	29,999	6,272	4,913	4,986	268	73,339
Caption length	29,999	120	120	11.0	70	166
Engagement rate	29,999	0.0421	0.0406	0.0241	0.00	0.271
Post frequency	29,999	1,502	1,494	51.8	1,392	1,599
Impressions	29,999	8,467	6,595	6,826	327	105,203
Hashtags count	29,999	7.99	8	2.83	0	21
Post hour	29,999	11.5	12	6.90	0	23
Followers gained	29,999	502	501	290	0	1,000

Note. N = 29,999 valid observations for each numerical variable; 1,000 observations were missing. SD = standard deviation.

The descriptive results show that 29,999 valid observations were available for each numerical variable. Engagement rate had a mean of 0.0421 and a median of 0.0406, with values ranging from 0 to 0.271. Follower count had a mean of 10,278, while the mean reach and impressions were 6,272 and 8,467, respectively. Caption length had a mean and median of 120, with values ranging from 70 to 166. The mean number of hashtags was 7.99, with observations ranging from 0 to 21 hashtags. Posting hour ranged from 0 to 23, with a mean of 11.5 and a median of 12. The

mean number of followers gained was 502, with values ranging from 0 to 1,000. Post frequency ranged from 1,392 to 1,599, with a mean of 1,502.

4.2 Distribution of Categorical Variables

To provide an overview of the categorical characteristics of the dataset, frequency distributions were examined for account type, time of day, media type, content category, call-to-action presence, day of the week, and traffic source. The distributions provide the composition of the observations across the different categories used in subsequent analyses.

Table 4.2
Frequency Distribution of Account Type

Variable	Counts	% of Total	Cumulative %
Brand	9,055	30.2%	30.2%
Creator	20,944	69.8%	100.0%

Table 4.3
Frequency Distribution of Time of Day

Variable	Counts	% of Total	Cumulative %
Night	7,444	24.8%	24.8%
Morning	7,547	25.2%	50.0%
Afternoon	7,554	25.2%	75.2%
Evening	7,454	24.8%	100.0%

Table 4.4
Frequency Distribution of Media Type

Variable	Counts	% of Total	Cumulative %
Carousel	10,627	35.4%	35.4%
Image	11,927	39.8%	75.2%
Reel	7,445	24.8%	100.0%

The categorical distributions indicate that creator accounts represented 69.8% of the observations, while brand accounts accounted for 30.2%. The findings may therefore show creator-account patterns more prominently than brand marketing behaviour. This means brands should interpret their applicability cautiously. Posts were distributed relatively evenly across time-of-day categories, with morning and afternoon accounting for 25.2% each, followed by evening and night at 24.8% each. Images were the most common media type at 39.8%, followed by carousels at 35.4% and reels at 24.8%. Each content category represented approximately 10% of the observations. Calls to action appeared in 34.9% of posts and were absent from 65.1%. Posts were also distributed consistently across the days of the week, ranging from 14.0% on Sunday to 14.5% on Tuesday, Wednesday, and Thursday. Traffic sources were similarly balanced, ranging from 16.2% for Explore to 16.9% each for Home Feed and Hashtags.

4.3 Engagement by Content Type

To examine whether engagement rate differed across different media types, a one-way analysis of variance (ANOVA) was conducted comparing carousel, image, and reel posts. Engagement rate was used as the dependent variable, while media type was treated as the grouping variable.

Table 4.9
One-Way ANOVA of Engagement Rate by Media Type

Variable	F	df1	df2	p
engagement_rate	1.10	2	29,996	.332

Table 4.10
Group Descriptives of Engagement Rate by Media Type

Media Type	N	Mean	SD	SE
Carousel	10,627	0.0418	0.0239	2.31e-4
Image	11,927	0.0423	0.0240	2.20e-4
Reel	7,445	0.0423	0.0245	2.84e-4

Table 4.11
Levene's Test of Homogeneity of Variance for Engagement Rate

Variable	F	df1	df2	p
engagement_rate	0.0952	2	29,996	.909

The mean engagement rate was 0.0418 for carousel posts, compared with 0.0423 for both image and reel posts. A one-way ANOVA found no statistically significant difference in engagement rate across carousel, image, and reel posts, $F(2, 29,996) = 1.10$, $p = .332$, $\eta^2 \approx .00007$. Levene's test was also non-significant, $F(2, 29,996) = 0.095$, $p = .909$, indicating that the assumption of homogeneity of variances was satisfied. Tukey post-hoc comparisons similarly showed no statistically significant pairwise differences, with all adjusted p-values exceeding .05.

These results should be interpreted as an absence of a detected difference between carousel, image and reel posts within this dataset, rather than as evidence that media format has no bearing on engagement more broadly. The analysis was limited to three broad format categories and did not capture finer-grained characteristics such as video length, editing style, opening hooks or thumbnail quality, any of which could plausibly influence engagement independently of the format label itself. It is also possible that format-specific effects exist at the individual account level but are obscured when averaging engagement rate across 20 accounts with different audiences and content styles. Consequently, the appropriate conclusion is that no statistically significant difference in engagement rate was detected between media types within this sample, not that content format is unrelated to engagement in general.

4.4 Optimal Posting Time

To examine whether engagement rate differed according to the time of day at which posts were published, a one-way analysis of variance (ANOVA) was conducted across four time-of-day categories: night, morning, afternoon, and evening. Engagement rate was treated as the dependent variable and time of day as the grouping variable.

Table 4.12
One-Way ANOVA of Engagement Rate by Time of Day

Variable	F	df1	df2	p
engagement_rate	1.23	3	29,995	.297

Table 4.13
Group Descriptives of Engagement Rate by Time of Day

Time of Day	N	Mean	SD	SE
Night	7,444	0.0425	0.0242	2.81e-4
Morning	7,547	0.0419	0.0241	2.78e-4
Afternoon	7,554	0.0421	0.0241	2.77e-4
Evening	7,454	0.0419	0.0240	2.78e-4

Table 4.14
Levene's Test of Homogeneity of Variance for Engagement Rate

Variable	F	df1	df2	p
engagement_rate	0.393	3	29,995	.758

The mean engagement rate was highest for posts published at night ($M = 0.0425$, $SD = 0.0242$), followed by afternoon posts ($M = 0.0421$, $SD = 0.0241$). Morning and evening posts recorded similar mean engagement rates ($M = 0.0419$). However, the one-way ANOVA indicated that these differences were not statistically significant, $F(3, 29,995) = 1.23$, $p = .297$, $\eta^2 \approx .00012$. Levene's test was also non-significant, $F(3, 29,995) = 0.393$, $p = .758$, indicating that the assumption of homogeneity of variances was satisfied.

4.5 Engagement by Content Category

To examine whether engagement rate differed across content categories, a one-way analysis of variance (ANOVA) was conducted across the ten content categories: Beauty, Comedy, Fashion, Fitness, Food, Lifestyle, Music, Photography, Technology, and Travel. Engagement rate was treated as the dependent variable, while content category was treated as the grouping variable. Descriptive statistics were examined alongside the ANOVA results and Levene's test of homogeneity of variance.

Table 4.15
One-Way ANOVA of Engagement Rate by Content Category

Variable	F	df1	df2	p
engagement_rate	1.17	9	29,989	.309

The ANOVA results indicated that the differences in mean engagement rate across the ten content categories were not statistically significant, $F(9, 29,989) = 1.17, p = .309$. The effect size was also very small ($\eta^2 \approx .00035$), indicating that content category accounted for only a negligible proportion of the variation in engagement rate.

Table 4.16
Group Descriptives of Engagement Rate by Content Category

Content Category	N	Mean	SD	SE
Beauty	2,953	0.0422	0.0249	4.57e-4
Comedy	2,950	0.0419	0.0233	4.29e-4
Fashion	3,034	0.0426	0.0240	4.36e-4
Fitness	3,004	0.0427	0.0245	4.47e-4
Food	3,010	0.0421	0.0248	4.53e-4
Lifestyle	3,017	0.0416	0.0230	4.20e-4
Music	3,003	0.0428	0.0249	4.55e-4
Photography	3,035	0.0415	0.0240	4.36e-4
Technology	3,025	0.0420	0.0240	4.35e-4
Travel	2,968	0.0417	0.0234	4.29e-4

The group means were relatively similar across the ten categories. Mean engagement rate ranged from 0.0415 for Photography to 0.0428 for Music. Fitness recorded a mean engagement rate of 0.0427, followed by Fashion at 0.0426, while Beauty, Food, Technology, Comedy, Lifestyle, and Travel recorded means of 0.0422, 0.0421, 0.0420, 0.0419, 0.0416, and 0.0417, respectively. The standard deviations ranged from 0.0230 to 0.0249 across the categories.

Table 4.17
Levene's Test of Homogeneity of Variance for Engagement Rate

Variable	F	df1	df2	p
engagement_rate	1.08	9	29,989	.375

Levene's test was non-significant, $F(9, 29,989) = 1.08, p = .375$, indicating that the assumption of homogeneity of variance was satisfied.

4.6 Engagement by Posting Month

To examine whether engagement rate varied across the observation period, a one-way analysis of variance (ANOVA) was conducted using posting month as the grouping variable and engagement rate as the dependent variable. The analysis included 13 monthly groups, covering November 2024 to November 2025.

Table 4.18
One-Way ANOVA of Engagement Rate by Posting Month

Variable	F	df1	df2	p
engagement_rate	0.894	12	29,986	.553

The results indicate that engagement rate did not differ significantly across posting months, $F(12, 29,986) = 0.894$, $p = .553$, $\eta^2 \approx .00036$. Therefore, the observed variation in mean engagement rates across months does not provide sufficient statistical evidence of a difference in engagement associated with posting month.

Table 4.19
Group Descriptives of Engagement Rate by Posting Month

Post Month	N	Mean	SD	SE
2024-11	1,004	0.0413	0.0227	7.17e-4
2024-12	2,532	0.0423	0.0236	4.70e-4
2025-01	2,587	0.0419	0.0233	4.59e-4
2025-02	2,322	0.0414	0.0242	5.02e-4
2025-03	2,499	0.0430	0.0252	5.04e-4
2025-04	2,509	0.0420	0.0239	4.76e-4
2025-05	2,579	0.0416	0.0230	4.52e-4
2025-06	2,494	0.0424	0.0253	5.07e-4
2025-07	2,535	0.0418	0.0231	4.58e-4
2025-08	2,509	0.0419	0.0243	4.85e-4
2025-09	2,320	0.0426	0.0243	5.04e-4
2025-10	2,532	0.0424	0.0243	4.83e-4
2025-11	1,577	0.0425	0.0257	6.48e-4

Descriptively, the mean engagement rate was highest in March 2025 ($M = 0.0430$), followed by September 2025 ($M = 0.0426$) and November 2025 ($M = 0.0425$). The lowest mean engagement

rate was observed in November 2024 ($M = 0.0413$). Overall, however, the monthly means remained relatively close to one another.

Table 4.20
Levene's Test of Homogeneity of Variance for Engagement Rate

Variable	F	df1	df2	p
engagement_rate	1.36	12	29,986	.178

Levene's test was non-significant, $F(12, 29,986) = 1.36$, $p = .178$, indicating that the assumption of homogeneity of variances was satisfied. Tukey post-hoc comparisons showed no statistically significant pairwise differences between any pair of months, with all adjusted p-values exceeding .05 (ranging from .559 to 1.000). These findings suggest that engagement rate remained stable across the thirteen-month observation period, with no evidence of a seasonal or time-based trend.

4.7 Correlation Analysis

Pearson's correlation coefficients were computed to examine the linear associations between engagement rate and the continuous content, publishing and account characteristics included in the study. The analysis considered posting frequency, posting hour, caption length, hashtag count, follower count, followers gained and reach.

Table 4.21
Correlation Matrix of Engagement Rate and Numerical Variables

Variable	1	2	3	4	5	6	7	8
1. Engagement rate	—							
2. Post frequency	0.004	—						
3. Post hour	-0.007	0.000	—					
4. Caption length	0.000	-0.004	0.011	—				
5. Hashtags count	-0.001	-0.004	0.004	0.000	—			
6. Follower count	-0.006	-0.116***	0.003	0.000	0.006	—		
7. Followers gained	0.001	0.007	0.002	-0.003	-0.004	0.013*	—	
8. Reach	0.006	-0.006	0.007	0.003	0.002	0.002	-0.005	—

Note. $N = 29,999$ for all correlations ($df = 29,997$). * $p < .05$, ** $p < .01$, *** $p < .001$.

The correlation matrix indicated that engagement rate was not significantly linearly associated with any of the continuous variables examined. The correlation between engagement rate and post frequency was negligible and non-significant, $r(29,997) = .004$, $p = .492$, as were the correlations with post hour, $r = -.007$, $p = .221$; caption length, $r = .000$, $p = .931$; hashtags

count, $r = -.001$, $p = .829$; follower count, $r = -.006$, $p = .330$; followers gained, $r = .001$, $p = .930$; and reach, $r = .006$, $p = .284$.

Two statistically significant correlations emerged among the predictor variables themselves, though both were negligible in magnitude. Post frequency was significantly negatively correlated with follower count, $r(29,997) = -.116$, $p < .001$, and follower count was significantly positively correlated with followers gained, $r(29,997) = .013$, $p = .028$. Given their very small effect sizes, neither association is likely to be of practical importance. Overall, the correlation analysis found no evidence of a meaningful linear relationship between engagement rate and any of the numerical content, publishing or account characteristics examined in this dataset.

4.8 Engagement by Day of Week

To examine whether engagement rate varied across different days of the week, a one-way analysis of variance (ANOVA) was conducted with day of week as the grouping variable and engagement rate as the dependent variable. The analysis included seven groups representing Monday through Sunday.

Table 4.22
One-Way ANOVA of Engagement Rate by Day of Week

Variable	F	df1	df2	p
engagement_rate	1.25	6	29,992	.275

The results indicated that engagement rate did not differ significantly across days of the week, $F(6, 29,992) = 1.25$, $p = .275$. Therefore, there is insufficient statistical evidence to conclude that the day of the week is associated with differences in engagement rate.

Table 4.23
Group Descriptives of Engagement Rate by Day of Week

Day of Week	N	Mean	SD
Friday	4,218	0.0424	0.0244
Monday	4,279	0.0416	0.0235
Saturday	4,254	0.0421	0.0240
Sunday	4,205	0.0425	0.0240
Thursday	4,351	0.0419	0.0247
Tuesday	4,351	0.0427	0.0249
Wednesday	4,341	0.0416	0.0232

Descriptively, the highest mean engagement rate was observed on Tuesday ($M = 0.0427$), followed by Sunday ($M = 0.0425$) and Friday ($M = 0.0424$). The lowest mean engagement rates were observed on Monday and Wednesday (both $M = 0.0416$). However, these differences were small and were not statistically significant.

Table 4.24
Levene's Test of Homogeneity of Variance for Engagement Rate

Variable	F	df1	df2	p
engagement_rate	0.850	6	29,992	.531

Levene's test indicated that the assumption of homogeneity of variances was satisfied, $F(6, 29,992) = 0.850$, $p = .531$. Thus, the standard one-way ANOVA results can be interpreted without concern regarding unequal variances. Because the overall ANOVA was not statistically significant, Tukey post-hoc comparisons were not conducted.

4.9 Multiple Regression Analysis

A multiple linear regression was conducted to examine the combined relationship between engagement rate and the full set of content, publishing and account characteristics specified in Section 3.5.5: follower count, followers gained, posting hour, hashtag count, caption length, account type, media type, content category, traffic source and call-to-action presence. Reach was not entered as a predictor, as it is used in the calculation of engagement rate and would therefore introduce circularity into the model. Categorical predictors were entered using reference categories (brand for account type, carousel for media type, Beauty for content category, Explore for traffic source, and absence of a call to action for call-to-action presence).

The overall regression model was not statistically significant, $F(24, 29,974) = 1.00$, $p = .458$, and accounted for a negligible proportion of the variance in engagement rate ($R^2 = 8.02e-4$; adjusted $R^2 \approx 0.000002$). This indicates that, considered jointly, the eleven content, publishing and account characteristics examined did not meaningfully predict engagement rate within this dataset.

Table 4.25
Model Fit Measures for the Multiple Regression Model

Model	R	R^2	Adjusted R^2	F	df1	df2	p
1	0.0283	8.02e-4	2.05e-6	1.00	24	29,974	.458

Table 4.26

Omnibus ANOVA Test for the Multiple Regression Model

Predictor	Sum of Squares	df	Mean Square	F	p
post_frequency	2.00e-4	1	2.00e-4	0.344	.557
post_hour	8.75e-4	1	8.75e-4	1.507	.220
caption_length	7.52e-6	1	7.52e-6	0.013	.909
hashtags_count	3.41e-5	1	3.41e-5	0.059	.809
follower_count	5.03e-4	1	5.03e-4	0.866	.352
followers_gained	5.27e-6	1	5.27e-6	0.009	.924
account_type	1.45e-5	1	1.45e-5	0.025	.874
media_type	0.00124	2	6.20e-4	1.068	.344
content_category	0.00607	9	6.74e-4	1.162	.315
traffic_source	0.00411	5	8.22e-4	1.416	.215
has_call_to_action	9.10e-4	1	9.10e-4	1.567	.211
Residuals	17.402	29,974	5.81e-4		

Consistent with the overall model result, none of the eleven predictors reached statistical significance at $\alpha = .05$. The largest, though still non-significant, effects were observed for traffic source, $F(5, 29,973) = 1.42$, $p = .215$, and content category, $F(9, 29,973) = 1.16$, $p = .315$. All remaining predictors, including media type, $F(2, 29,973) = 1.07$, $p = .344$, produced smaller and similarly non-significant effects.

Table 4.27

Model Coefficients for Engagement Rate

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	p	Std. Est.
Intercept (a)	0.0396	0.00445	0.03091	0.04835	8.908	<.001	—
post_frequency	1.59e-6	2.71e-6	-3.72e-6	6.89e-6	0.587	.557	0.00341
post_hour	-2.48e-5	2.02e-5	-6.43e-5	1.48e-5	-1.227	.220	-0.00709
caption_length	1.44e-6	1.26e-5	-2.33e-5	2.62e-5	0.114	.909	6.58e-4
hashtags_count	-1.19e-5	4.92e-5	-1.08e-4	8.45e-5	-0.242	.808	-0.00140
follower_count	-1.95e-8	2.09e-8	-6.05e-8	2.15e-8	-0.931	.352	-0.00541
followers_gained	4.57e-8	4.79e-7	-8.94e-7	9.85e-7	0.095	.924	5.51e-4
account_type: creator – brand	4.79e-5	3.03e-4	-5.46e-4	6.42e-4	0.158	.874	0.00199
media_type: image – carousel	4.25e-4	3.22e-4	-2.06e-4	0.00105	1.320	.187	0.01762
media_type: reel – carousel	4.27e-4	3.64e-4	-2.87e-4	0.00114	1.171	.242	0.01771
content_category: Comedy – Beauty	-3.49e-4	6.27e-4	-0.00158	8.81e-4	-0.556	.578	-0.01447
content_category: Fashion – Beauty	4.03e-4	6.23e-4	-8.18e-4	0.00162	0.647	.518	0.01672
content_category: Fitness – Beauty	5.35e-4	6.24e-4	-6.89e-4	0.00176	0.857	.391	0.02221
content_category: Food – Beauty	-1.14e-4	6.24e-4	-0.00134	0.00111	-0.183	.855	-0.00474
content_category: Lifestyle – Beauty	-5.51e-4	6.24e-4	-0.00177	6.72e-4	-0.883	.377	-0.02285
content_category: Music – Beauty	6.08e-4	6.25e-4	-6.16e-4	0.00183	0.974	.330	0.02524
content_category: Photography – Beauty	-7.42e-4	6.23e-4	-0.00196	4.79e-4	-1.191	.234	-0.03079
content_category: Technology – Beauty	-1.63e-4	6.24e-4	-0.00138	0.00106	-0.261	.794	-0.00676
content_category: Travel – Beauty	-5.13e-4	6.26e-4	-0.00174	7.15e-4	-0.819	.413	-0.02130
traffic_source: External – Explore	4.28e-4	4.85e-4	-5.23e-4	0.00138	0.882	.378	0.01776
traffic_source: Hashtags – Explore	-1.02e-4	4.84e-4	-0.00105	8.46e-4	-0.211	.833	-0.00423
traffic_source: Home Feed – Explore	-3.60e-4	4.83e-4	-0.00131	5.87e-4	-0.745	.456	-0.01495
traffic_source: Profile – Explore	6.47e-4	4.86e-4	-3.06e-4	0.00160	1.331	.183	0.02685
traffic_source: Reels Feed – Explore	5.51e-4	4.85e-4	-3.99e-4	0.00150	1.138	.255	0.02287
has_call_to_action: 1 – 0	-3.66e-4	2.92e-4	-9.38e-4	2.07e-4	-1.252	.211	-0.01517

No individual predictor reached statistical significance at $\alpha = .05$. The largest standardized effects were observed for content category (Photography relative to Beauty, $\beta = -0.031$, $p = .234$) and media type (reel relative to carousel, $\beta = 0.018$, $p = .242$), though both remained well short of significance. All standardized estimates were small in magnitude ($|\beta| < 0.04$), indicating that even the largest observed effects would be of limited practical relevance.

Table 4.28
Collinearity Statistics for the Multiple Regression Model

Predictor	VIF	Tolerance
post_frequency	1.01	0.993
post_hour	1.00	1.000
caption_length	1.00	1.000
hashtags_count	1.00	1.000
follower_count	1.01	0.993
followers_gained	1.00	0.999
account_type	1.00	1.000
media_type	1.00	1.000
content_category	1.00	1.000
traffic_source	1.00	1.000
has_call_to_action	1.00	1.000

Collinearity diagnostics indicated no concern regarding multicollinearity among the predictors. All variance inflation factors (VIF) were at or near 1.00 and all tolerance values exceeded .99, well within conventional thresholds ($VIF < 5$; tolerance $> .20$).

Assumption Checks

The Q-Q plot of standardized residuals showed a marked departure from normality in the upper tail, with residuals

curving sharply above the reference line beyond approximately 1.5 theoretical quantiles. The residuals-versus-fitted plot similarly showed evidence of heteroscedasticity: the majority of residuals formed a dense, evenly scattered band close to zero, but a distinct subset of posts produced substantially larger positive residuals, creating a non-constant spread across the range of fitted values. This pattern was consistent across the residual plots for each individual predictor.

This pattern is consistent with the underlying distribution of engagement rate, which is bounded at zero and positively skewed, with the majority of posts clustered at low-to-moderate engagement and a comparatively small number of posts achieving disproportionately high engagement. Because ordinary least squares regression assumes normally distributed, homoscedastic residuals, these violations mean the standard errors, confidence intervals and p-values reported in Table 4.27 should be interpreted with caution. A more appropriate specification — such as a generalized linear model with a log or gamma link function, which better accommodates a bounded, positively skewed outcome like engagement rate — would likely produce more precise standard errors and confidence intervals than the ordinary least squares model used here. However, given that the overall model was already non-significant and all individual effect sizes were negligible, the substantive conclusion — that the content optimization factors examined here show no meaningful linear association with engagement rate in this dataset — is unlikely to change under a model better suited to the outcome's distribution (for example, a generalized linear model with a log or beta link function). This limitation is noted as a direction for methodological refinement in Section 3.7 rather than as a basis for revising the substantive findings.

5. Interpretation and Discussion

5.1 Interpretation of Key Findings

The findings of this study provide limited empirical support for the assumption that commonly recommended Instagram content optimization practices consistently translate into higher engagement rates. Across the analyses, engagement rate remained relatively stable, with no statistically significant differences associated with media type, content category, posting time, posting frequency, posting hour, caption length, hashtag usage, day of the week, or the other account and publishing characteristics examined. This pattern is important because the study was designed to test content optimization practices empirically rather than assume that individual practices necessarily improve performance. The research question therefore appears to be answered more by the absence of systematic relationships than by the identification of a single optimal strategy.

The analysis of media type did not provide evidence that one format consistently generated superior engagement. This finding is noteworthy given the strong emphasis placed on reels and other visual formats in contemporary social media marketing. Existing literature suggests that media richness can contribute to engagement, while industry research frequently reports strong performance for short-form video. However, academic evidence also indicates that the effectiveness of a format depends on the content and context in which it is used. The present

findings support the latter interpretation: format alone does not appear to explain meaningful variation in engagement rate within this dataset.

A similar pattern was observed for content category. Although descriptive differences existed, with Music recording the highest mean engagement rate and Photography the lowest, the differences were statistically insignificant, $F(9, 29,989) = 1.17$, $p = .309$, with a negligible effect size. This suggests that the thematic category of a post, considered in isolation, may not be sufficient to determine engagement performance. Rather than assuming that particular content niches inherently generate greater engagement, marketers may need to consider the execution, audience relevance and account-specific context surrounding the content.

The findings relating to posting time provide a similar qualification to conventional optimization advice. Night-time posts recorded the highest descriptive mean engagement rate, followed by afternoon posts, while morning and evening posts were similar. Nevertheless, the differences were not statistically significant, $F(3, 29,995) = 1.23$, $p = .297$. The correlation analysis also found virtually no linear relationship between posting hour and engagement rate ($r = -.007$, $p = .221$). This suggests that there is no single broadly applicable posting period that can be identified from this dataset. This is consistent with the literature, which argues that optimal posting time can vary according to account, audience, content and day.

The same conclusion applies to posting frequency, captions and hashtags. Posting frequency had an almost zero correlation with engagement rate ($r = .004$, $p = .492$), while caption length and hashtag count also demonstrated negligible and non-significant associations. This does not necessarily mean that captions or hashtags are irrelevant to social media performance. Existing literature suggests that the quality, relevance and characteristics of hashtags and textual content may matter more than their simple quantity or length. Thus, the results may indicate a limitation of treating these practices as easily measurable numerical optimization variables.

The month and day-of-week analyses further reinforce the stability of engagement rate. Monthly engagement differences were not significant, $F(12, 29,986) = 0.894$, $p = .553$, despite March 2025 recording the highest descriptive mean. Similarly, the day-of-week analysis found no statistically significant differences, $F(6, 29,992) = 1.25$, $p = .275$. Therefore, neither seasonal timing nor particular days of the week provided evidence of a reliable engagement advantage.

Most importantly, the multiple regression analysis demonstrates that these findings remain consistent when the predictors are considered simultaneously. The full model was not statistically significant, $F(24, 29,974) = 1.00$, $p = .458$, and explained only approximately 0.08% of the variance in engagement rate. None of the individual predictors reached statistical

significance. This provides stronger evidence that the absence of meaningful relationships is not simply a consequence of examining each factor separately.

5.2 Implications for Marketing Strategy

The findings suggest that social media teams should be cautious about treating content optimization as a fixed checklist in which posting at a particular time, using a particular format, increasing hashtags or changing caption length automatically produces higher engagement. The results instead support a more contextual approach in which optimization decisions are informed by the specific audience, account and content objective.

This does not imply that marketers should stop testing different formats, posting times or creative approaches. Rather, these practices should be treated as hypotheses to test, rather than universal rules. For example, although night-time posts had the highest descriptive engagement rate, the difference was not statistically supported. A brand could therefore use night-time publishing as a starting point for experimentation, but should validate the result using its own historical performance data rather than assuming that night is inherently optimal.

Similarly, the absence of a significant media-type effect suggests that brands should not adopt reels, carousels or images solely because one format is widely described as the highest-performing format. The objective and audience of the content should remain central to the format decision.

An important caveat: this study examines relationships averaged across 20 different accounts with potentially distinct audiences and strategies. The optimal posting time, format, or caption style for one account may differ substantially from another. Rather than treating findings as universal recommendations, each account should test these variables within its own data. Account-specific experimentation is likely more valuable than applying averaged results across diverse accounts.

5.3 Implications for Analytics and Measurement

From an analytics perspective, one of the most important findings is that descriptive performance differences should not automatically be interpreted as evidence of optimization effects. Several groups displayed different mean engagement rates, but these differences were consistently too small to establish statistically meaningful variation. The results also demonstrate the importance of considering multiple variables simultaneously. The regression model showed that even when content, publishing and account characteristics were entered together, their explanatory power remained negligible. This suggests that engagement rate may be influenced by factors not captured by the available variables, such as creative quality, audience sentiment, brand

familiarity, individual post topic, current events, algorithmic distribution or the strength of the creator-audience relationship.

The analytical results therefore support a shift from generic benchmarking toward account-specific experimentation and measurement. Rather than asking whether one universal posting time or content format performs best, social media teams could test alternative strategies within individual accounts and evaluate changes over time.

5.4 Limitations

Several limitations should be considered when interpreting the findings. First, the study uses a secondary dataset obtained from Kaggle, meaning that the analysis is restricted to the variables available in the dataset. Important determinants of engagement may therefore be absent.

Second, the study is observational. Consequently, the findings demonstrate statistical associations rather than causal effects. A non-significant relationship between posting time and engagement, for example, cannot establish that changing posting time would never affect engagement; it only indicates that a systematic relationship was not observed in this dataset.

Third, the dataset contains 29,999 valid observations but represents only 20 Instagram accounts, with repeated observations from the same accounts. The large number of posts therefore should not be interpreted as equivalent to a sample of 29,999 independent accounts.

Finally, the regression diagnostics indicated departures from normality and homoscedasticity. The engagement-rate distribution is positively skewed, with most observations concentrated at relatively low levels and a smaller number of substantially higher observations. Consequently, the regression standard errors and significance tests should be interpreted with caution. Future analyses could address this limitation by fitting a generalized linear models with a log or gamma link, which would better accommodate the bounded, positively skewed nature of engagement rate than ordinary least squares regression.

5.5 Alternative Explanations

The absence of significant relationships may reflect the fact that engagement is driven by more complex interactions than those captured by the measured optimization variables. For example, the effectiveness of a reel may depend on its creative quality, topic, opening hook, audience relevance and distribution rather than on the fact that it is a reel.

Similarly, the effect of a hashtag may depend on its relevance and competitiveness rather than simply the number of hashtags used. Another possibility is that account-level and audience-level characteristics play a greater role than the observable structural characteristics of individual

posts. The dataset contains repeated observations across accounts, and the literature reviewed in the study similarly emphasizes that content performance can vary according to audience and account context.

5.6 Relationship with Existing Literature

The findings do not necessarily contradict the existing literature; instead, they provide a more cautious interpretation of it. Previous research has identified relationships between particular content characteristics and engagement, but has also emphasized that these effects can be context-dependent. For example, research by Wahid and Gunarto (2021) found that carousel posts and questions could influence engagement, while other research has identified relationships between posting consistency and engagement.

The current study's results suggest that such relationships should not automatically be generalized across accounts and contexts. In particular, the absence of significant effects for posting frequency, timing, captions and hashtags indicates that recommendations based on these variables may have limited predictive value when applied universally.

Importantly, this absence of detectable effects within the present dataset should not be read as contradicting prior findings such as those of Wahid and Gunarto (2021); rather, it reflects the fact that different datasets, account types and observation periods can plausibly produce different results. The appropriate conclusion is therefore that content optimization effects appear to be context-dependent rather than universal, not that such effects do not exist.

5.7 Theoretical Contribution

The principal contribution of the study is therefore not the identification of a single optimal Instagram strategy, but the demonstration that commonly discussed optimization variables may have very limited explanatory power when examined across a broad set of posts and accounts. The findings support a contextual view of social media optimization. Content optimization should be understood as a multidimensional process rather than as a collection of universally effective tactics.

The results also reinforce the importance of distinguishing between descriptive patterns and statistically supported relationships. In this dataset, several apparent differences existed, but the inferential analyses consistently showed that these differences were too small to provide evidence of systematic effects.

Overall, the study suggests that Instagram engagement cannot be reliably predicted from basic content and publishing characteristics alone. Instead, effective optimization is likely to require

account-specific experimentation, richer measures of content quality and audience behaviour, and analytical approaches capable of capturing interactions and non-linear relationships.

6. Recommendations & Actionable Insights

6.1 For Marketing Practitioners

Quick wins (implement now): Because this dataset found no statistically significant difference between carousel, image and reel formats, or any single best-performing posting hour, day or month, the highest-value immediate action is not to chase a specific format or timing formula. Instead, practitioners should redirect effort toward factors this study could not measure but which the literature identifies as plausible engagement drivers — creative execution, opening hooks, editing quality and thumbnail design. A diversified posting schedule maintained consistently is a more defensible default than concentrating output around an assumed "optimal" hour.

Medium-term strategy (1–3 months): Rather than standardizing captions around a specific length, brands should focus on caption clarity and relevance, since this study found caption length itself unrelated to engagement. Building a structured content calendar that intentionally varies format, timing and messaging in a controlled, trackable way allows an account to generate its own evidence base, rather than relying on generic industry benchmarks that this dataset does not support.

6.2 For Analysts/Analytics Teams

A useful measurement framework tracks engagement rate at the account level over time rather than pooling across accounts, since this study's account-level averaging may obscure effects that exist within individual accounts. Testing protocols should favor within-account experimentation — for example, alternating posting times or formats for a single account over successive weeks — over cross-account comparisons, which are vulnerable to the confounding this study encountered. Dashboards should flag when observed differences are within the range of statistical noise, to prevent teams from reacting to descriptive fluctuations that are not reliably distinguishable from chance.

6.3 For Marketing Managers

The business case here is reallocation rather than new spend: budget currently directed at chasing universal "best time to post" or "best format" guidance is not supported by this evidence and could be redirected toward creative production quality and account-specific testing infrastructure. The investment required is primarily analytical (testing tooling, consistent tracking) and creative (production quality), rather than a wholesale content strategy overhaul.

Projected returns cannot be quantified causally from this data, but the expected return on continuing to follow unproven generic rules is likely low, while the return on account-specific experimentation, though uncertain, is more likely to reflect that account's actual audience.

6.4 Limitations of Recommendations

These recommendations are drawn from an observational dataset of 20 accounts on a single platform over one year, and apply most directly to accounts with a similar profile. They should not be assumed to generalize to substantially larger or smaller accounts, other platforms, or different time periods, and should be piloted on a small scale before being adopted as policy.

6.5 Future Research Directions

Future research could incorporate quantified measures of creative and visual quality, account age and history, and audience composition; use experimental rather than purely observational designs to establish causality; and apply models such as fractional logit or beta regression with appropriate treatment of zero values to better accommodate the bounded and skewed distribution of engagement rate.

7. Conclusion

7.1 Research Summary

This study asked to what extent content optimization factors — media type, posting time, posting frequency, caption length, hashtag usage and call-to-action presence — are associated with Instagram engagement performance. Across descriptive, correlational, ANOVA and regression analyses of nearly 30,000 posts from 20 accounts, no statistically significant relationship was found between engagement rate and any of the optimization factors examined.

7.2 Main Takeaways

First, none of the structural content characteristics tested — including media type, $F(2, 29,996) = 1.10$, $p = .332$, and posting time, $F(3, 29,995) = 1.23$, $p = .297$ — showed a significant relationship with engagement rate. Second, the full multiple regression model, incorporating eleven content, publishing and account-level variables, explained less than 0.1% of the variance in engagement rate, $F(24, 29,974) = 1.00$, $p = .458$. Third, while descriptive differences existed across formats, times, categories and days, all were too small to be statistically distinguished from chance at this sample size. Fourth, this pattern is better read as evidence that engagement is context-dependent and driven by factors outside this dataset, rather than as proof that content optimization is irrelevant.

7.3 Significance

For the marketing industry, these findings temper the tendency to treat generic "best practice" advice as universally applicable. For analytics practice, they reinforce the value of account-specific, hypothesis-driven testing over benchmarking against aggregate industry data.

7.4 Practical Value

Brands and creators stand to gain more from treating optimization tactics as testable hypotheses within their own account and audience than from adopting external rules about format, timing or caption length. Resources may be better directed toward creative quality and audience relevance than toward structural adjustments this study found no evidence for.

7.5 Limitations Restatement

These conclusions are drawn from a secondary, observational dataset covering 20 Instagram accounts over a single one-year period, and are subject to the distributional and diagnostic limitations discussed in Section 5.4; they should be read as account-specific patterns rather than universal principles.

7.6 Future Implications

As richer creative-quality data becomes available and as platforms and algorithms continue to evolve, future work using experimental designs and account-level modeling is better positioned to isolate what actually drives Instagram engagement.

7.7 Final Statement

In an environment where content decisions are increasingly made in the name of data, this study's central contribution is a reminder of what data-driven marketing should actually mean: testing assumptions against evidence, rather than treating unexamined assumptions as fact.

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