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Modeling social media engagement efficiency in tourism: A multi-platform analytical approach

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ABSTRACT

The purpose of the study is to determine the impact of social media tourism content on viewer engagement. To understand if the structured content is able to get higher levels of impressions, likes, shares, and interactions. It uses the concept of the Content Structural Efficiency (CSE) model in determining how structured tourism content can be improved in social media for Indian State Tourism Boards. This research uses a quantitative approach and real-life data collected from more than 70 social media pages of Indian State Tourism Agencies. The data comprises 7258 posts that result in 3.8 million engagement activities. The statistical techniques have been applied to evaluate the engagement rate on each platform and to determine the efficiency of content structure using the CSE framework. The finding proves that there exists variation in engagement level and content types among all the channels. It can be seen that the contents which are well-structured, designed in an effective manner, and consistent received higher engagement in contrast to content that is unstructured or improperly formatted. This study contributes to the existing research in the field of tourism marketing and social media. The introduction of the Content Structural Efficiency (CSE) model can be considered as a new approach to measuring the efficiency of content across all the various platforms. Besides that, it is possible to conclude that the suggestions made are quite practical regarding the development of content marketing strategies in tourism.

Contribution/Originality: The paper contributes the first logical analysis to tourism and social media literature by developing a systematic theme-based classification framework for tourism content and linking each content theme with its most effective structural design for engagement optimization. Unlike prior studies focusing solely on content categories or performance metrics, this research integrates thematic segmentation with platform-specific content structure recommendations.

1. INTRODUCTION

Information and Communication Technology (ICT) has played a crucial role in the business operations of service sectors like the tourism industry. Social media platforms nowadays have become more powerful tools for marketing, which further help decide travel decisions (Ammirato, Felicetti, Linzalone, & Carlucci, 2022). The destination marketing organizations (DMOs) and tourism businesses use social media to connect with potential customers (Yuan, Chan, Eichelberger, Ma, & Pikkemaat, 2026).

In the tourism industry, social media acts as a platform both for users and service providers to share content. Tourists post their feedback, reviews, and experiences, which provide real-time information about the trends and preferences (Gulati, 2022). A study on online reviews in Turkey stated that regular feedback on destinations highlights the pros and cons of the destination for further actions, and this study shows that engagement on the posts is equally important (Çatir & Ayvazoğlu, 2025). Although there has been extensive work carried out on the use of social media marketing in the tourism industry, an essential research gap still exists, which is to effectively emphasize the role that the structural composition of the content can play in influencing engagement. Most studies have mainly focused on the classification of content such as informational, emotional, or promotional content and its effect on engagement (Coelho, de Oliveira, & de Almeida, 2016; Dolan, Seo, & Kemper, 2019; Tsimonis & Dimitriadis, 2014).

In this study, there was an attempt to determine the type of content that could be considered engaging in the field of tourism and investigate the role of certain factors, such as the form of posts (text, photo, and video), the themes of the content posted, and timings that impact engagement. From prior literature, it can be noted that visuals perform better, and posts having either pictures or videos generate more engagement than posts with text. In various researches about the performance of posts of destination marketing organizations, it was shown that themes of destinations differed in engagement depending on whether the theme was nature, cultural, or events. Furthermore, the results showed that posts published on social networking platforms, like Facebook, by tourist authorities were better accepted when presented through visual media during weekends. However, there have been instances when DMOs post their content on social media platforms randomly, with no strategy behind them, and the implication from that is the inadequacy of the marketing campaigns carried out by DMOs since it fails to maximize the engagement of the target audiences because of the failure to apply content that works effectively.

In an effort to fill this gap in research, the study used the Content Structural Efficiency (CSE) model, which was proposed by Saikia and Barman (2022), and adapted it for tourism. The CSE model is examined with regards to 7,258 social media posts of 70 Indian State Tourism pages on Facebook, Twitter, Instagram, and YouTube. A number of variables, such as content type, content theme, behavior type, level of user participation, and audience type, were analyzed to determine how to structure the content in a manner that will improve engagement levels (María, Ruiz, & Saura, 2025; Moran, Muzellec, & Johnson, 2020; Shahbaznezhad, Dolan, & Rashidirad, 2021). Whereas previous studies have investigated either theme or format in isolation, there appears to be little information about how the different elements interact to impact engagement. Hence, by adopting CSE framework that takes into account multiple factors in content design, the study helps to close the identified research gap. Specifically, by investigating the impact of tourism content on social media engagement, this paper brings together different findings obtained during the literature review process and integrates them into one comprehensive study. Moreover, application of CSE model to social media tourism content proves that CSE framework can also be used not only for education but also for other fields, especially dynamic areas with a lot of people interaction like tourism. From both theoretical and practical points of view, the study conducted has its merits. First of all, the research has provided theoretical grounds for evaluation of the effectiveness of social media content regarding its engagement. Secondly, there are some practical implications for marketers working in the field of tourism as well: knowledge of users' preferences on the specific social media site may be useful.

2. LITERATURE REVIEW

2.1. Importance of Social Media in Tourism

Social media has a significant impact on tourist destination decisions. According to Chatterjee and Dsilva (2021), the use of social media in tourism marketing can help to improve the reputation of a place and when compared to traditional media techniques, tourist locations can reach out to potential visitors at a cheaper cost and with greater efficiency. The widespread use of social media and online travel networks fosters virtual conversations and, in some cases, influences traveller decisions. The tourist online recommendations over social media impact the destination decisions of potential visitors (Chatzigeorgiou, 2017; Gulati, 2022). The relevance of online activity by service providers helps in building better customer perception (Meng, Dipietro, Gerdes, Kline, & Avant, 2018). Customers can benefit from digital marketing in a variety of ways, including staying up to date with products or services, greater engagement, clear information about products and services (Mkwizu, 2020; Shu, Wu, & Li, 2023). Bala and Verma (2018) conducted a critical assessment of digital marketing to identify present and future marketing trends in India. According to the report, there has been a significant shift toward digitalization, with customers browsing and exploring more on the internet for the greatest deals. In addition, knowing which social media sites a company's target market uses is an important component in ensuring that online marketing is successful (Mkwizu, 2020).

2.2. Importance of Content Theme

The role of content categories in shaping audience engagement on social media has been extensively examined across diverse research contexts. Prior studies have indicated that specific content categories are more effective in stimulating audience activity and interaction (Coudounaris et al., 2025; Lipsman, Mudd, Rich, & Bruich, 2012). For instance, studies carried out by Chandrasekaran, ShabbirHusain, and Annamalai (2024), Alboqami et al. (2015), and Dolan et al. (2019) have revealed that entertainment-related content performs better in terms of increasing engagement compared to other types of content on social media platforms. In addition to that, engagement does not seem to be equal for all types of content since different types of performance are exhibited under different contextual circumstances (Tsimonis & Dimitriadis, 2014). Beyond content categories, the format or type in which content is presented has also emerged as a critical determinant of engagement on social media. Several empirical studies have investigated the influence of content type on user interaction and engagement behaviour across platforms. For instance, Shahbaznezhad et al. (2021) examined the impact of content type on engagement levels on Facebook and Instagram, using 'likes' and 'comments' as key indicators of audience response.

Therefore, the null hypothesis for testing the impact is as follows:

$H_0 1_{tp}$: There is no significant difference in the engagement level of content theme within the platform.

Where *t* is the theme and *p* is the platform.

2.3. Importance of Content-Type

Kaplan and Haenlein (2010) suggested that a high-media-rich post has a better capability of generating engagement. A highly interactive post generates a high volume of engagement (De Vries, Gensler, & Leeflang, 2012; Fortin & Dholakia, 2005). A hybrid content format can instigate higher-order user engagement over social media (Daugherty, Eastin, & Bright, 2008). The format of the content has a direct influence on user engagement (Schmidt, Pempek, Kirkorian, Lund, & Anderson, 2008). A clearer image or photo shared over social media can generate a high volume of like engagement over social media, whereas a video would generate comments (Kim, Best, & Choi, 2023; Shahbaznezhad et al., 2021). The findings of the said researchers suggest that content category has a direct impact on user engagement. Specific content categories are likely to generate a higher level of engagement over social media based on the platform. Social media positively impacts consumer decision-making regarding sustainable purchases with communication, specifically social influence and perceived trust, playing a critical role in shaping these decisions (Arora, Rana, & Prashar, 2023; Čuić, Kapeš, & Fućak, 2025). Ashley and Tuten (2015) considered likes and comments to measure user engagement. Similarly, many studies have kept the scope of the platform limited to either one or two platforms, specifically Facebook and Twitter (now X) (Coelho et al., 2016; Dolan et al., 2019; Pletikosa & Michahelles, 2013; Tafesse, 2015). The study in digital marketing shows that innovative contents and interactive content can significantly improve engagement performance, but depending on the context, audience characteristics, and platform dynamics (Janssen, Schouten, & Croes, 2022). Further, Li and Xie (2020) states that incorporating visual content significantly enhances engagement outcomes, as posts that include images tend to generate higher levels of user interaction compared to text-only formats. This study considers four social media platforms namely Facebook, Twitter (now X), YouTube, and Instagram; therefore, the most common post formats have been selected for the analysis.

Therefore, the null hypothesis for testing the impact is formulated as:

H_o2_{ij}: Post type has no significant impact on Engagement.

Where i is the theme and j is the platform.

2.4. Importance of Perceived Action

Earlier research defined Perceived Action as the audience's desired behavior that aims to inspire involvement. Some academics believe that perceived activity is a positive effect of a post and a necessary interaction for content consumption (Sheng, Lee, & Lan, 2024). Prior research suggests that increasing levels of interactivity through participatory actions can enhance user involvement and stimulate engagement by encouraging active participation (Moran et al., 2020; Pandit, McLeay, Zaveri, Al Mursalin, & Rosenberger, 2025). Some studies also argue that empirical evidence suggests that a poorly aligned interaction may lead to cognitive overload leading to a negative impact on engagement outcomes (Rietveld, Van Dolen, Mazloom, & Worring, 2020; Tafesse, 2015; Yuan & Lou, 2020). The variation in results implies that the impact of perceived action is neither uniform nor deterministic. Instead, interactivity has been seen as creating positive or negative effects on engagement, depending on contextual factors (Nikolinakou & Phua, 2024). Furthermore, researchers have argued that interactivity into varying levels of complexity (De Vries et al., 2012). Such as low, moderate, and high, indicating that different forms of content may not yield consistent engagement outcomes across contexts (Moran et al., 2020; Tafesse, 2015). Building on this theoretical foundation (Saikia & Barman, 2022) suggested four levels of Perceived Action namely Interaction, Participation, Subscription, and Conversion, to capture varying degrees of user involvement in the context of higher educational sector. The present study extends the same framework and intends to explore its applicability with tourism content across platforms. Therefore, to empirically assess its significance within the current framework, the following null hypothesis is proposed.

Therefore, the null hypothesis for testing the impact is as follows:

H_o3_{ij}: Perceived Action has no significant impact on Engagement.

Where i is the theme and j is the platform.

2.5. Importance of User Involvement

User Involvement refers to the degree of cognitive involvement required from users to process and interact with social media content. Earlier studies conceptualise involvement as a multidimensional construct that significantly shapes how users experience and respond to digital content (Souki, Chinelato, & Gonçalves Filho, 2022; Zhang & Li, 2025). That means that more involvement, along with greater demand for engagement will produce better results because it will bring more user involvement. But modern studies have shown that involvement and engagement are not directly connected. Therefore, the nature of involvement results in different performances based on specific individual or platform conditions (Ashfaq et al., 2026; Oh & Pham, 2022). Also, demands for different types of involvement differ from one another due to the nature of different content types. So, while image-based content can easily be processed cognitively, videos need a lot of mental involvement (Bansal & Sisodia, 2026; Waqas, Salleh, & Hamzah, 2021). As follows from that statement, the involvement can be understood as a factor initiated by users as well as different content types. In some cases, such involvement can become excessive, thus leading to cognitive overload and reduced attention (Mazerant, Willemsen, Neijens, & van Noort, 2021; Zhang & Li, 2025). However, due to the heterogeneity in how different levels of involvement convert into observable engagement indicators, the independent influence of user involvement is unclear. Therefore, to empirically assess its significance within the present analytical framework, the following null hypothesis is proposed.

Therefore, the null hypothesis for testing the impact is as follows:

H_o4_{ij}: User Involvement has no significant impact on Engagement.

Where i is the theme and j is the platform.

2.6. Importance of Target Audience

Target audience is defined as the subset of the larger target market, refined by demographics, habits, psychographics, and location to enable personalized, successful, and efficient advertising campaigns. In contemporary digital marketing concepts, audience targeting is recognised as a critical step for enhancing content relevance and engagement by aligning messages with user preferences, behavioural patterns, and platform-specific audience profiles. The present literature highlights that audience-platform alignment and segmentation techniques greatly affect brand post engagement, suggesting that content efficacy is partly influenced by audience segmentation (Shen, 2023). Even though the strategic importance is highlighted but the conceptualised theory of target audience as a structural determinant of engagement is not yet completely developed. Limited study found on examine engagement through content or platform characteristics, with limited attention given to audience orientation as an independent variable. Furthermore, recent evidence reveals that engagement outcomes are influenced by a variety of interconnected elements such as platform affordances, algorithmic distribution, and content design, diminishing the solitary explanatory power of audience targeting (Pieter & Angelopoulos, 2024). This study fills the gap in the literature by operationalizing Target Audience according to the three types of directional appeal as Internal, External, and Not Specified in order to understand the structural function of target audience in content creation. The independent influence of the target audience is still theoretically unclear, nevertheless, due to the lack of consistent empirical confirmation and the multifactorial nature of interaction. Hence, the following null hypothesis is put out to empirically investigate its significance within the current framework.

Therefore, the null hypothesis for testing the impact is as follows:

H_o5_{ij}: *Target Audience has no significant impact on Engagement.*

Where i is the theme and j is the platform.

2.7. Selection Engagement Attributes

The analytical dimension of social media platforms is powered by analytics dashboards, which are inbuilt in most cases for e.g., Facebook Insight for Facebook. Precisely, these dashboards work based on the data a page or account generates through its platform interaction attributes. That means for analytics, one has to look within the scope of the functionality of the platform. The built-in dashboards and third-party tools like Hootsuite and HubSpot use metrics for formulating trends and interpreting patterns in engagement. Studies have explicitly mentioned the importance of metrics and their interpretation for social media analytics (Ambler & Roberts, 2008; Benthaus, Risius, & Beck, 2016; Peters, Chen, Kaplan, Ognibeni, & Pauwels, 2013). The page interaction helps to understand the details of the engagement pattern (Bambauer-Sachse & Einsle, 2025; Bonsón & Ratkai, 2013; Hoffman & Fodor, 2010). To understand how these platforms work, one has to go by the details of the principle algorithm or the content placement mechanism a platform has in place. For Facebook, it works primarily based on some signals which as a result determine the display of content to its users (Forouzandeh, Sheikhahmadi, Rezaei Aghdam, & Xu, 2018; Newberry, 2019). Content engagement through platform interaction attributes remains a key component of the Facebook algorithm (Barnhart, 2022; Oremus, Alcantara, Merrill, & Galocha, 2021). McLachlan (2020) suggested that similar to Facebook, the reach and impressions of content get regulated through some signals on Instagram. The signals for content display over Instagram are designed for conditional activation based on circumstances (Mosseri, 2021).

2.8. Classification of Content Based on Theme

The process of classifying social media content has been discussed in detail in Practical Text Analytics (Anandarajan, Hill, & Nolan, 2019), where both inductive and deductive approaches are explained in a clear, step-by-step manner. In line with this, the present study adopts a similar combined inductive–deductive approach for content classification. The structure used for classification is based on earlier studies, particularly Shahbaznezhad et al. (2021), which builds on the brand post classification model developed by Tafesse and Wien (2017). The basic idea of dividing content into transformational and informational types was originally proposed by Puto and Wells (1984). This was further developed through more detailed sub-categories in studies such as Laskey, Day, and Crask (1989). These broad classifications have been successfully used in empirical studies conducted in the area of social media by Ashley and Tuten (2015).

In light of this, the present study employs the theoretical framework proposed by Tafesse and Wien (2017) to categorize the brand-related postings found in the tourism industry. This study collected posts from tourism-based social media accounts from various social media sites. Classification of these postings was done through the use of MAXQDA text analysis software. Clustering was made based on similarity.

A similarity cut-off point of 0.6 was set for the clustering. This similarity value is considered acceptable by Hennig (2007) since values higher than 0.6 imply thematic similarity, which makes the posts ideal for grouping. Consistency and reliability in the grouping process will be ensured by two independent reviewers coding the themes. The themes selected for this study, along with the content categories are given in Table 1.

Table 1. Content classification framework.

Categories	Transactional	Informational	Economical	Transformational
Subcategories	Conversion	Testimonials	Cost of Tour	Comparison
	Booking	Reviews	On Location Cost	
	Ads	Relationship	Cost of Food	
	Promotional			
	Transactional category includes those posts that ask for some level of conversions such as booking, buying etc Informational category includes those post that shares knowledge on some place or location, user experiences testimonials etc. Economical category includes those post that provides information on cost and budgeting related to any location or place. Transformational category includes those post that provides comparisons between two locations or places or hotels etc.			

2.9. Content Structural Efficiency for Tourism Content (CSE-Tourism)

The studies found the role of social media posts and user engagement in framing content strategies (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004; Keegan & Rowley, 2017; Moran et al., 2020; Pletikosa & Michahelles, 2013; Swani, Milne, & Brown, 2013). The brand post and users' response towards it have become very common connecting points between them. Based on this, further research has highlighted more content features such as format, tone, or structure affect engagement across platforms (Moran et al., 2020; Shahbaznezhad et al., 2021). Recent research has moved the focus from engagement to performance, rather than from the question of whether engagement occurs at all to the question of why certain content performs better than others. Further literature stated that researchers rely on interaction-based indicators such as likes, comments, and shares for measurement. De Vries et al. (2012) used the interaction metrics to understand user engagement behaviour and Muñoz-Expósito, Oviedo-García, and Castellanos-Verdugo (2017) suggested that engagement ratios can provide a more detailed and meaningful picture. Tourism marketing research spotlights that the content, audience, and platform all play a crucial role in shaping engagement (Lee, Lau, & Wong, 2023).

The existing literature lacks in explaining the structural interactions between various content components and their effects on engagement results because most of it has focused on individual content parts. However, to address this limitation, Saikia and Barman (2022) developed the concept of Content Structural Efficiency (CSE) to explain the combined effect of different content elements on engagement in social media platforms. Further studies have explained the influence of content characteristics such as type, theme, and appeal, and have proposed models to estimate the engagement-generating capacity of social media content (De Vries et al., 2012; Kumar, Mangla, Luthra, Rana, & Dwivedi, 2018; Moran et al., 2020; Tafesse, 2015). The existing studies largely focused on variables specific and descriptive studies. But the empirical work of Saikia and Barman (2022) conducted on educational content on Facebook offered a comprehensive methodological framework for assessing content structural efficiency, identifying five key structural elements: Content Theme (CoTh), Content Type (CoTy), Perceived Action (PA), User Involvement (UI), and Target Audience (TA). Their model conceptualised Content Theme as independent of structural configuration while being contingent on the intended target interaction. While tourism marketing research has developed robust classifications of content types and documented platform-level differences in engagement behaviour (Ashley & Tuten, 2015; Puto & Wells, 1984; Tafesse & Wien, 2017), the translation of these conceptual insights into integrated and quantifiable evaluative models remains underdeveloped. Recent studies underscore the importance of systematic content design in improving engagement efficiency in tourism communication (Amanatidis, Mylona, Mamalis, & Kamenidou, 2020), yet few have operationalised this principle through a holistic performance-based framework. In response to this gap, the present study applies the Content Structural Efficiency (CSE) model to tourism-related social media content, integrating content complexity with observed engagement metrics. By enabling a comparative assessment of how efficiently different content configurations generate audience interaction across platforms, the CSE framework extends existing literature beyond descriptive categorisation and contributes a data-driven, performance-oriented perspective to tourism social media research.

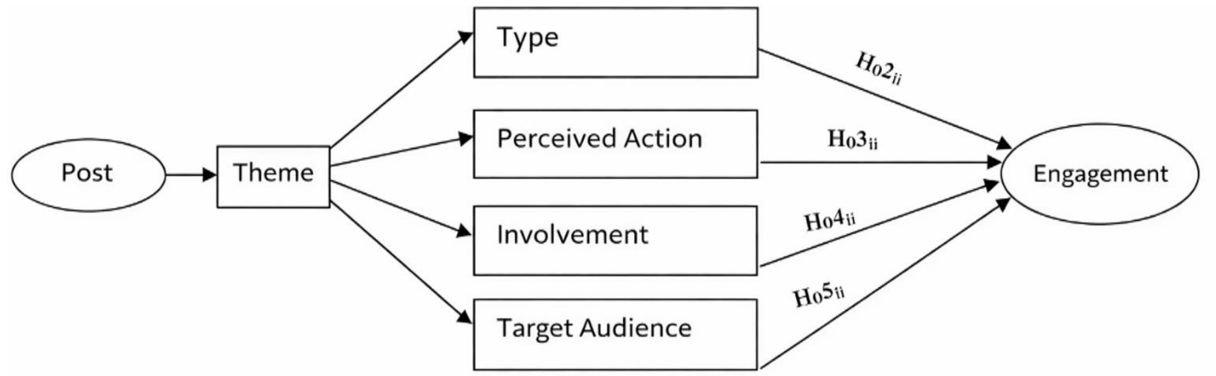

Figure 1. Content structural efficiency model (CSE model).

Figure 1 illustrates the basic structure of the content analysis framework. This study views the theme as being independent of structure and dependent on 'target interaction'. Thus, once the page has determined the specific interaction it wishes to target with a post, it must estimate the most contributing theme and adjust the structure accordingly. The following hypotheses were developed based on the literature review to support the importance of structural elements per 'target interaction'.

H_o2_{ij}: Post type has no significant impact on Engagement.

H_o3_{ij}: Perceived Action has no significant impact on Engagement.

H_o4_{ij}: User Involvement has no significant impact on Engagement.

H_o5_{ij}: Target Audience has no significant impact on Engagement.

Where 'i' is the type element and 'j' is the Engagement.

2.10. Research Questions

RQ1: Which content structural configurations demonstrate the greatest efficiency in generating user engagement with tourism-related posts across the selected social media platforms?

RQ2: Which social media platform proves most effective in optimising engagement for tourism-related content over the observed period?

2.11. Objectives of the Study

Based on the hypothesis and the capability of the framework used in this study, the following are the objectives of the study.

- Identify the most efficient content structure for tourism content engagement optimization.
- Identify the most effective social media platform for engagement optimization.

3. METHODOLOGY

3.1. Sampling

For the purpose of sampling all the social media pages of the Indian tourism ministry at the state level, the selected channels namely; Facebook, Twitter (now X), Instagram, and YouTube have been covered. Initially, all websites of Indian state tourism ministries were visited and linked social media handles were tracked. A further two-step sample filtration process was used to finalize the actual sample.

3.1.1. Sample Filtration

Step 1: The social media handles that were not verified and have no backlinks linking the page to the official websites were dropped.

Step 2: Secondly, the pages, which have activated privacy settings regarding data transparency were dropped. These accounts restrict any third-party tool from extracting page-level public access data. Hence it is not possible to track the post and engagement of such accounts without admin access. This study only includes publicly available data accessible through any third-party tool. Total count of sample stood at 70 pages across all platforms (Facebook – 17; Twitter (now X) – 23; Instagram – 15; YouTube – 15).

3.2. Data Collection

The data used in this study was collected in a structured manner, mainly to keep things consistent across platforms. At the same time, care was taken so that the process can be repeated if needed. The focus was on posts shared by official Indian state tourism department pages. Platforms like Facebook, Instagram, Twitter, and YouTube were considered, but only those posts that were publicly available were included. The data collection was done over a period of about three months, starting from 1 August 2025 and going up to 30 October 2025. This period was not randomly selected. It was important to exclude any irregularities that may be caused by holidays and weeks of intensive activities; otherwise, it would have been possible to see only sporadic behavior. From this point of view, the presented information corresponds to ordinary content performance.

To retrieve data, an online paid software known as Socialinsider.io was utilized. Each page had to be scraped manually through its unique Page ID, which consumed some time, but this was inevitable to ensure precision. The same date range was applied consistently since consistency in dates enables proper comparison between different sites. In this context, all posts made during this particular period of time were considered; no discrimination or selection based on types or formats was made in any case. Engagement information was gathered for each individual post made. However, the overall approach to data collection was kept the same. This helped maintain consistency, even though the nature of engagement may vary from one platform to another.

3.3. Analytical Framework

The overall analysis of the study was grouped into two broad categories; namely, content type and content theme. Initially, a descriptive analysis of the content type and theme was carried out to understand the overall pattern of engagement per platform. Further, the effect of content on engagement across the selected platforms was analysed using content efficiency (engagement per post) and content contribution. The efficiency of the content defines its ability to generate engagement against page activity level and contribution helps in estimating the content category's share of the overall engagement. Kruskal–Wallis test was then used to estimate the statistical significance of the engagement level generated by each category per platform. Lastly, negative binomial regression analysis was carried out to estimate the combined impact of content type and theme on engagement per platform.

3.3.1. Content Efficiency

The study was carried out on 'post level' data per platform. This helps in understanding the level of engagement and pattern of engagement a platform produces based on the type of activity. The following equations have been used to calculate the efficiency rate and contribution rate of content type and theme per platform. The efficiency for each content theme and type for each platform was calculated separately. The following equation has been used for calculating the $C_{on}Ef$.

$$Ef_{ijp} = \frac{Content\ Engagement\ for\ category\ 'j'}{Total\ number\ of\ post\ in\ the\ category\ 'j'} \qquad (1)$$

Where i = Content, j = Category and p = Platform.

For Facebook (j)= Text, Image, and Video.

For Instagram (j)= Carousel, Image and Video.

For Twitter (now X) (j)= Text, Image and Video.

For YouTube (j)= Video.

3.3.2. Content Contribution ($C_{on}Ct$)

The contribution for each content category was calculated for each platform separately. The contribution value for the content category explains the ability of the content category to contribute towards overall engagement by the sample within a platform. The following equation was used for determining the content contribution.

$$C_{on}Ct_{ijp} = \frac{Total\ Engagement\ by\ a\ Content\ Category}{Total\ Platform\ Engagement} \qquad (2)$$

3.4. Kruskal–Wallis Test

The study intends to identify the most effective content type in terms of generating engagement to enhance the platform's efficiency. To understand the statistical significance of the difference in engagement level for each content type and theme per platform, Kruskal–Wallis test was carried out. As explained above, the study considers the platform-supported content type; hence, content category (type and theme) was considered as independent variables and engagement was considered as the dependent variable. The content category was rated based on its complexity as defined by earlier studies (De Vries et al., 2012; Moran et al., 2020; Tafesse, 2015). According to these studies, a simple 'Text' post has the lowest complex structure and is thus rated 1, while a 'Video' content is the most complex and is thus rated 4. The variables' rating has been done as per the CSE model. Kruskal–Wallis test has been carried out at two levels – firstly to understand the difference in the engagement level of content type and theme within the platform and secondly to understand the difference in the engagement level of content type and theme across platforms; namely, cross-platform difference.

3.5. Parameter Estimates for Content Structural Efficiency

The impact of content structure on engagement has been studied using negative binomial regression. For analysis and mathematical convenience, the CSE model uses a converted 'Pi ratio' instead of raw data. Since the 'Pi Ratio' is considered to be an acceptable metric for analysing post engagement capabilities, as it is calculated based on Post Reach and Engagement per Reach and the analytical equations for processing the data set, specifically 'Pi ratio' was suggested by Muñoz-Expósito et al. (2017). Studies like Coxe, West, and Aiken (2009) and Tafesse (2015) provide details on using logistic regression and Benoit (2011) discussed the log transformation in case of non-normal distribution. Most of the real-time web data are non-normal in nature so was the case with this study; therefore, the data has been transformed using the following equation.

$$log\ (Y_{ej})\ =\ \alpha_e\ +\ \{\sum \beta_1\ log\ (PE_{j1})\ +\ \beta_2\ log\ (PE_{j2})\ +\ \dots\dots\dots\ +\ \beta_n\ log\ (PE_{jn})\ +\ \varepsilon_i \quad (3)$$

Where log (Y_{ej}) indicates the log of engagement (e) for posts 1, 2, 3, and so on. β_1, β_2, β_3, β_4, β_n indicates the regression coefficient for log (PE_{tn}), and log (PE_{t1}) represents the post-exposure for post j=1,2,3,4, and so on.

For parameter estimates, this study uses the CSE model equation as suggested by Saikia and Barman (2022) for Content Structural Efficiency based on recommendations by previous research (Hilbe, 2014; Moran et al., 2020).

$$Y_{ij} = exp\ \beta\ (\sum \beta_o\ +\ \beta_{Type\ tj}X1j\ +\ \beta_{Perceived\ Action\ aj}X2j\ +\ \beta_{Target\ Audience\ nj}X3j\ +\ \beta_{Involvement\ zj}X4j) \quad (4)$$

Where, Y_{ij} => Y_{1j} or Y_{2j} or Y_{3j} or Y_{4j}; log of post like, share, comment, and reaction respectively, exp β_{zi} is the equation regression coefficient obtained as parameter estimates (z = element).

3.5.1. Ratings for Content Structural Elements

The Table 2 highlights the classification and quantification approach of the study used for transforming non-count variables into count variables, which is a necessary step for conducting statistical analysis. As illustrated in Table 2, key conceptual constructs such as Type, Perceived Action, User Involvement, and Target Audience, which are inherently qualitative in nature, have been systematically operationalised into measurable count variables through a structured rating scheme. All the variables have been rated according to the complexity, interaction, or involvement of the construct in increasing order to enable their integration into mathematical models. The rating scale draws on data from research works like those of Tafesse (2015); De Vries et al. (2012); Moran et al. (2020) and Calder and Malthouse (2009). The process is also subjective on the part of the authors so that the appropriateness of the context can be ensured. This is important because it will facilitate the application of statistics to abstract variables along with engagement.

Table 2. Non-count variables rating.

S. No.	Variable Type			
	Element	**Non- count**	**Categories** **Refer Table 1**	**Rating**
1	Theme			N/A
2	Type*	Count	Text	1
			Link	2
			Photo	3
			Album/Carousel	4
			Video	5
3	Perceived Action*	Count	Click	1
			Interaction	2
			Subscription	3
			Conversion	4
4	User Involvement*	Count	View	1
			Listen	2
			Read	3
			Participate	4
5	Target Audience*	Count	Internal	1
			External	2
			Not Specified	3

Note: *Non-Count variables converted to count.
Source: Tafesse and Wien (2017); Tafesse (2015); Moran et al. (2020); De Vries et al. (2012); Tafesse (2015); Moran et al. (2020); Calder and Malthouse (2009); Alboqami et al. (2015) and Newberry (2019).

4. DATA ANALYSIS

4.1. Content Classification and Post Allocation

The content classification has been done based on the calculated similarity score obtained from the inter-coder analysis based on the categorization done by three independent reviewers. Table 3 presents the similarity and inter reliability score for the themes and sub-themes. The similarity scores obtained from the analysis ranged between 0.50

to 0.66, which indicates moderate to high level of acceptance of post allocation (Tafesse & Wien, 2017). More importantly, the Inter-coder reliability index (I) demonstrates strong reliability across all sub-categories, with values ranging between 0.71 and 0.82. The highest agreement is observed in sub-categories such as *Testimonials* (I = 0.82) and *Reviews* (I = 0.81), suggesting these content types possess clearer semantic boundaries and are more consistently identifiable across reviewers. The categories that fall within comparatively lower agreement, such as *Relationship* (*I* = 0.71), also obtained an acceptable threshold, reflecting a high level of agreement. The consistently high reliability index reinforces the validity of the content categorization process, thereby strengthening the credibility of subsequent analyses derived from this framework.

Table 3. Content similarity results and post allocation.

Categories	Study Content Classification Framework			
	Transactional	**Informational**	**Economical**	**Transformational**
Sub Categories	Conversion (0.6*,0.54**,I=0.73, n=842)	Testimonials (0.66*,0.52**, I=0.82, n=624)	Cost of Tour (0.53*,0.62**, I=0.76, n=489)	Comparison (0.61*,0.53**, I=0.78, n=601)
	Booking (0.51*,0.58**, I=0.79, n=796)	Reviews (0.51*,0.54**, I=0.81, n=701)	On Location Cost (0.61*,0.52**, I=0.77, n=452)	
	Ads (0.56*,0.5**, I=0.81, n=915)	Relationship (0.53*,0.61**, I=0.71, n=548)	Cost of Food (0.55*,0.62**, I=0.77, n=416)	
	Promotional (0.63*,0.55**, I=0.76, n=874)			

Note: * indicates the intra-sub-category similarity and ** indicates inter sub-category similarity.

4.2. Content Type Description

Table 4 illustrates the descriptive analysis of content type performance (efficiency) and contribution based on the values obtained using equations 1 and 2. The analysis suggests that 'Video' is the most efficient content type over Facebook with an efficiency of 977.7 and a marginal efficiency of 794.65 over the nearest content type (Image). The average efficiency for Facebook was recorded to be 440. 'Text' was observed to be the most inefficient content type on Facebook with just 160 efficiency ratings and 0.02 contribution, which is 2 percent of the total engagement over Facebook. Similarly, Instagram 'Carousel' was observed as the most efficient content type with a 1659 efficiency rating; however, the marginal efficiency with 'Image' was extremely low at 40.8. Although 'Video' was observed as the most inefficient content type over Instagram, it still generated a higher volume of engagement with a better efficiency rating when compared to other platforms. 'Image' is the most contributing content type over Instagram with almost 59 percent of engagement being generated through 'Image' content. For Twitter (now X), 'Video' was observed to be the most efficient content type with the highest rating at 470 and a marginal rating of 248 with 'Text'. Here 'Text' and 'Image' can be considered similarly efficient with just a marginal difference of 0.95.

Table 4. Content type efficiency and contribution.

Platform	Content Type Analysis					
	Content-Type	Performance			Contribution	
		Engagement	Post	Efficiency	Engagement	Post
Facebook	Text	14404	90	160.04	0.02	0.04
	Image	297363	1624	183.11	0.42	0.76
	Video	401861	411	977.76	0.56	0.19
Instagram	Carousel	463088	279	1659.81	0.21	0.21
	Image	1233656	762	1618.97	0.59	0.58
	Video	411852	267	1542.52	0.20	0.20
Twitter (now X)	Text	327950.7	1476	222.19	0.33	0.42
	Image	248447.5	1123	221.24	0.25	0.32
	Video	417391.8	887	470.57	0.42	0.25
YouTube	Video	33578	339	99.05	N/A	N/A

Note: N/A implies Not Applicable for the Platform

4.3. Content Theme Descriptive

4.3.1. Efficiency

The content theme efficiency analysis suggests that 'Transformational and 'Entertainment' content has the highest efficiency over Facebook and 'Transaction' content was the lowest for any given format except for 'Transformational-Image' and 'Transactional-Text'. For Instagram, highest efficiency was recorded for 'Entertainment-Video' at 2949, followed by 'Informational-Carousel' at 2454. Relatively the average efficiency for the 'Theme-Type' combination over Instagram was observed to be much higher when compared to other platforms. The lowest efficiency was recorded for 'Informational-Video' at 270, followed by 'Transactional-Video' at 321. For Twitter (now X), the highest efficiency was recorded for 'Entertainment-Video' at 669, followed by 'Transactional-Video' at 625. The lowest efficiency was recorded for 'Transactional-Text' at 140. The results have been illustrated in Table 5.

Table 5. Content theme efficiency.

Content Theme Efficiency					
Platform	**Content-Type**	**Informational**	**Transformational**	**Transactional**	**Entertainment**
Facebook	Text	507.55	175.82	76.43	0.00
	Image	167.53	82.81	126.22	311.61
	Video	517.66	1641.06	202.49	1438.55
Instagram	Carousel	2454.79	1247.19	1961.79	1370.92
	Image	1700.24	1444.59	1662.28	1644.84
	Video	270.31	1955.64	321.20	2949.17
Twitter (Now X)	Text	324.99	229.02	140.85	225.81
	Image	201.95	221.33	367.78	180.85
	Video	504.49	230.64	625.41	669.91
YouTube	Video	124.30	107.00	0.00	91.47

4.3.2. Contribution

The theme contribution analysis suggests contribution for Facebook was made by 'Entertainment' content with 'Image' at 23 percent and 'Video' at 30 percent. The lowest contributions were made by 'Text' content across the content theme categories for Facebook at just 1 percent. It is also the lowest contribution obtained across the platforms except 'Informational-Video' for Instagram. The highest contribution for Instagram was recorded for 'Entertainment-Image' at 20 percent, followed by 'Informational-Image' at 16 percent. For Twitter (now X), the highest contribution was recorded for 'Entertainment-Video' at 14 percent, followed by 'Informational-Video' at 11 percent. The lowest was recorded for 'Transactional-Image' at 5 percent. For YouTube, 'Entertainment' made the highest contribution with 70 percent of the total engagement, followed by 'Informational' with 27 percent. It is interesting to find that the least efficient category also has the highest consolidated contribution across the platform. This finding suggests that high post frequency for a content type can dilute efficiency even though it is generating a high volume of engagement. The results have been illustrated in Table 6.

Table 6. Content theme contribution.

Theme Contribution					
Platform	**Content-Type**	**Informational**	**Transformational**	**Transactional**	**Entertainment**
Facebook	Text	0.01	0.01	0.01	0.00
	Image	0.08	0.05	0.05	0.23
	Video	0.04	0.19	0.04	0.30
Instagram	Carousel	0.07	0.04	0.04	0.08
	Image	0.16	0.11	0.12	0.20
	Video	0.01	0.05	0.01	0.12
Twitter (now X)	Text	0.09	0.08	0.06	0.10
	Image	0.07	0.06	0.05	0.06
	Video	0.11	0.07	0.09	0.14
YouTube	Video	0.27	0.03	0.00	0.70

4.3.3. Interpretation of Theme-Wise Engagement Differences Across Platforms

The Kruskal-Wallis test was performed to see whether different forms of content result in varying degrees of engagement. This test is useful for comparing more than two groups, particularly when the data does not strictly follow a normal distribution. This study analyzed four forms of content: informative, transformational, transactional, and entertainment. Each of them was investigated separately for Facebook, Instagram, Twitter (now X), and YouTube. After conducting the test, the data revealed no significant difference in engagement across different content genres on any of the platforms. The value of H for all four cases was 3.00, while the p-value was 0.392, which exceeds the threshold value of 0.05. Therefore, from the statistical perspective, there is no statistically significant difference between these themes in terms of involvement. The interesting part comes when these results are compared to the overall measures of engagement. For instance, information-related posts performed better than transactional and entertainment-based posts in terms of overall interaction. From an initial perspective, these results suggest that there is a possibility of some forms of content performing better than others. But, contrary to this assumption, the statistical results indicate otherwise. Variations in overall posts are not enough to determine a trend in this regard. In practical terms, audience participation in tourism marketing is not heavily dependent on the type of content presented. Although one form seems to perform better than others, this could change over time. Therefore, marketers would benefit from engaging various types of content in their work.

4.4. Kruskal–Wallis Test

4.4.1. Kruskal–Wallis Test — Within Platform

The results obtained from the Kruskal–Wallis test suggest significant differences in engagement levels among content types on Facebook (p = 0.000) and Twitter (p = 0.000). However, for Instagram, no statistically significant difference was observed (p = 0.880), which suggests uniform engagement across Carousel, Image, and Video formats. Since YouTube includes only one content type (Video), the test was not applicable.

The null hypotheses for equal engagement levels among content types were thus rejected for Facebook ($H_0$1fb) and Twitter ($H_0$1tw) and accepted for Instagram ($H_0$1inst). Table 7 presents the Kruskal–Wallis test results for content types within platforms and Table 8 presents Pairwise Comparisons Within Platform.

Table 7. Kruskal–Wallis test – content type by platform.

Platform	df	H Statistic	p-value	Result
Facebook	2	24.57	0.000	Significant
Instagram	2	0.25	0.88	Not Significant
Twitter (now X)	2	21.71	0.000	Significant

To identify specific group differences, Dunn's post hoc test with Bonferroni correction was conducted. On Facebook, engagement from Video content was significantly different from both Image (p = .000) and Text (p = .047). No significant difference was observed between Text and Image (p = .997). For Twitter, Video also differed significantly from both Text (p = .000) and Image (p = .023), while Text and Image showed marginal non-significance (p = .051). For Instagram, all pairwise comparisons were non-significant.

Table 8. Dunn's post hoc comparisons (Bonferroni-adjusted).

Platform	Pairwise Comparison	p-value	Significance
Facebook	Video vs Image	0.000	Significant
	Video vs Text	0.047	Significant
	Image vs Text	0.997	Not Significant
Instagram	All Pairwise Comparisons	>0.05	Not Significant
Twitter (now X)	Video vs Image	0.023	Significant
	Video vs Text	0.000	Significant
	Image vs Text	0.051	Not Significant

4.4.2. Kruskal–Wallis Test — Content Type Across Platforms

To evaluate whether the same content type performs differently across platforms, a Kruskal–Wallis test was conducted for Image, Text, and Video categories across Facebook, Instagram, Twitter (now X), and YouTube (where applicable). The findings suggest significant differences in engagement for each content type across platforms, as illustrated with Table 9 and Table 10 presents the Post Hoc Comparisons Across Platforms.

Table 9. Kruskal–Wallis test – content type across platforms.

Content Type	Platforms	df	H Statistic	p-value	Result
Image	FB, IG, TW	2	269.48	0.000	Significant
Text	FB, TW	1	15.93	0.000	Significant
Video	FB, IG, TW, YT	3	5.45	0.001	Significant

Post hoc tests for content type across platforms revealed that the statistical comparisons reveal key differences in how audiences engage with similar content types across social media platforms. Image content on Instagram performs better than on Facebook and Twitter (now X), as indicated by a highly significant difference in engagement levels ($p < 0.001$). The results obtained from the analysis suggest that the user expectations make it highly effective for image-based tourism content on Instagram. Similarly, Video content on Instagram outperforms Twitter ($p = 0.016$) and YouTube ($p = .001$) which suggests Instagram's strength for differences in engagement compared to Instagram ($p=0.416$) or YouTube ($p = 0.051$); the close threshold p-value in the latter case suggests a potential engagement gap. Overall, these findings reinforce the need to adapt content format strategies to platform-specific audience behaviour, with Instagram emerging as the most versatile platform for both image and video content in the context of tourism engagement.

Table 10. Dunn–Bonferroni post hoc comparisons across platforms.

Comparison	p-value	Significance
Image IG vs FB	0.000	Significant
Image IG vs TW	0.000	Significant
Video IG vs TW	0.016	Significant
Video IG vs YT	0.001	Significant
Video FB vs IG	0.416	Not Significant
Video FB vs YT	0.051	Not Significant
Text FB vs TW	0.000	Significant

The Kruskal–Wallis results confirm platform-specific differences in how content types generate engagement. While Facebook and Twitter showed significant variability across content types with Video consistently outperforming other formats, Instagram exhibited stable engagement across all types. Cross-platform analysis reaffirmed that Instagram's Image and Video content generated higher engagement compared to the same formats on other platforms. These findings support the broader conclusion that content strategies should be tailored to platform behaviour, and content type selection significantly impacts engagement outcomes.

4.5. Parameter Estimates for Content Elements

The total content structural efficiency for Facebook was estimated according to Equation 4 using the β values provided in Table 11. As expected, there is a strong positive influence of video content on all types of interaction, confirming previous research results about higher attractiveness of visual content in tourism communication (Ashley & Tuten, 2015). The perception of action category shows more shares and reactions (respectively, $\beta = 1.091$ and $\beta = 1.249$) for subscription appeals, indicating that posts encouraging further interaction have a higher probability of being distributed. As for interaction cues of users, it should be mentioned that 'Read' is a cue that contributes significantly to Shares ($\beta = 2.559$), showing that even now, informational posts have power in encouraging users to redistribute the content. In turn, there is no influence of 'Listen' on such interaction types as Likes (β = 0.458) and Shares (β = 0.663), probably due to the reluctance of users to engage with audio content while browsing through the internet. Though 'Read' positively impacts Likes and Comments, the relationship between this variable and Reactions is rather weak (β = 0.463), and it is possible to state that not all informational posts evoke users' emotions. Regarding target audiences, almost all groups correlate positively with interaction types except 'External' (β = 0.872) and 'Not specified' (β = 0.961) in relation to Comments.

For Instagram, similar observations are made about the higher engagement rates generated by videos among all interactions. It can be explained by the high priority of images and short videos in such social networks. Carousel posts have demonstrated the decrease in Shares (β = 0.541). The reason might be the low interest of the users in posts containing multiple images, which require swiping several times. As far as images, they result in increased commenting (β = 1.034). Static photos can provoke users' actions in comments, even though they cause a decrease in the other interaction types, probably because there are no dynamics and no interactions in the posts. In relation to perceived action type, all post categories except interaction have shown decreased engagement (β = 1.254). It means that users like to perform simple actions instead of complicated activities. In the user interaction category, only the participation type of content positively influences engagement (β = 1.338). Moreover, Not Specified posts demonstrate an increase in Shares (β = 1.145) and Comments (β = 1.237).

In the case of Twitter, there is a slight variation in results. Only image content is found to enhance engagement in all three measures of interaction, supporting the hypothesis that even in the predominantly textual platform, images play an integral role. In contrast, videos demonstrate a negative influence on all aspects of interaction, perhaps because of reasons like loading times and users' preferences. In regard to perceived actions, there are few variations; while Likes (β = 2.375) and Reactions (β = 1.254) increase with interaction cues, the rest of the interaction measures experience negative effects on engagement. This might mean that users can be engaged up to a certain extent, but they do not have much interest in interacting more intensively. User interactions also do not have much positive impact, as their effect on engagement is not significant, because no β value exceeds 1. Neither does target audience segmentation show any positive results.

For YouTube, the presence of many videos as the primary content leads to an increment in likes (β = 1.237) and shares (β = 1.228), therefore leading to greater levels of activity from its members. At the same time, comments demonstrate a decreasing trend (β = 0.348), which might suggest passive consumption of content. In terms of actions perceived by the viewers, positive correlations for interaction and conversions were found. Interaction promotes likes (β = 2.375) and shares (β = 1.276), whereas conversions promote shares (β = 1.275) and dislikes (β = 1.334). In terms of user interaction, only participation shows a positive effect, particularly for Shares (β = 1.376) and Dislikes (β = 1.337), while other interaction types show a negative effect, reinforcing the idea that engagement on YouTube is selective and often depends on how strongly users are encouraged to participate.

Table 11. Parameter estimates for each platform.

Platform	Variable Category	Element / Category	Engagement Type	β Estimate
Facebook	Content Type	Video	All interactions	2.017*
	Perceived Action	Subscription	Shares	1.091**
		Subscription	Reactions	1.249*
	User Interaction	Read	Shares	2.559*
		Listen	Likes	0.458**
		Listen	Shares	0.663*
		Read	Reactions	0.463*
	Target Audience	External	Comments	0.872**
		Not Specified	Comments	0.961*
Instagram	Content Type	Video	All interactions	2.374**
		Carousel	Shares	0.541*
		Image	Comments	1.034*

Platform	Variable Category	Element / Category	Engagement Type	β Estimate
	Perceived Action	Interaction	Engagement	1.254**
	User Interaction	Participation	Engagement	1.338*
	Target Audience	Not Specified	Shares	1.145**
		Not Specified	Comments	1.237*
Twitter (X)	Content Type	Image	All interactions	0.812*
		Video	All interactions	0.612**
	Perceived Action	Interaction	Likes	2.375*
		Interaction	Reactions	1.254*
	User Interaction	All types	All interactions	0.589**
	Target Audience	All	All interactions	0.823*
YouTube	Content Type	Video	Likes	1.237*
		Video	Shares	1.228*
		Video	Comments	0.348**
	Perceived Action	Interaction	Likes	2.375*
		Interaction	Shares	1.276*
		Conversion	Shares	1.275*
		Conversion	Dislikes	1.334**
	User Interaction	Participation	Shares	1.376*
		Participation	Dislikes	1.337*

Note: *Significance at 0.05 and **significance at 0.01; ($p < 0.05$, 0.01 = null hypothesis rejected).

As discussed within the analysis section Table 12 illustrates the hypothesis testing summary and the most optimized content structure for each platform and illustrates the acceptance and rejection of each hypothesis obtained from the test.

Table 12. Hypothesis testing summary.

Hypothesis	Platform	Significant Variables Identified	p-value Level	Hypothesis Result
$H_0$2ij Post Type	Facebook	Video*, Image*	$p < 0.05$	Rejected
	Instagram	Video*, Carousel**, Image*	$p < 0.01$ / $p < 0.05$	Rejected
	Twitter (X)	Image*, Video**	$p < 0.01$ / $p < 0.05$	Rejected
	YouTube	None Significant	$p > 0.05$	Accepted
$H_0$3ij Perceived Action	Facebook	Interaction**, Subscription*, External*	$p < 0.01$ / $p < 0.05$	Rejected
	Instagram	Conversion*, Subscription*, Not Specified**	$p < 0.01$ / $p < 0.05$	Rejected
	Twitter (X)	Subscription*, External*, Not Specified*	$p < 0.05$	Rejected
	YouTube	None Significant	$p > 0.05$	Accepted
$H_0$4ij User Involvement	Facebook	Participate*, Read**, Listen*	$p < 0.01$ / $p < 0.05$	Rejected
	Instagram	Read*	$p < 0.05$	Rejected
	Twitter (X)	Read*	$p < 0.05$	Rejected
	YouTube	None Significant	$p > 0.05$	Accepted
$H_0$5ij Target Audience	Facebook	External*, Not Specified*	$p < 0.05$	Rejected
	Instagram	External*, Not Specified**	$p < 0.01$ / $p < 0.05$	Rejected
	Twitter (X)	External*, Not Specified*	$p < 0.05$	Rejected
	YouTube	None Significant	$p > 0.05$	Accepted

Note: *Significance at 0.05 and **significance at 0.01; ($p < 0.05$, 0.01 = null hypothesis rejected).

5. CONCLUSION

The volume of activity and engagement specific to a platform suggests that publishers aggressively favour some form of content type over others. In aggregate, all the pages through all the social media platforms have generated an engagement volume of 3849592 for the given 7258 activity levels with an approximate efficiency of 530. Considering aggregate efficiency as a benchmark for tourism content over social media, in general, only three types of content across two platforms have generated better efficiency. The aggregate volume of the engagement generated by each platform suggests Instagram is the most effective platform through volume and efficiency. Instagram generated an aggregate engagement volume of 2108596 against an activity level of 1308 with an efficiency of 1613, followed by Facebook, which generated an aggregate engagement volume of 684820 against an activity volume of 2125, generating an efficiency of 323. Twitter (now X), however, is the most active platform with a high level of activity of 3489 and an engagement volume of 993790 with an efficiency of 286. YouTube is the least active platform and the lowest in terms of engagement volume. It generated an efficiency of 0.27. The activity-performance ratio for each content type per platform suggests that 'Video' over Facebook is the most efficient content type with a rating of 2.94. That means the engagement contribution is 2.94 times more than the activity share 'Video' for published content. That means the amount of shares a particular content holds for publication correlates to the level of engagement it generates for the platform. That can also be observed through the correlation estimates between engagement and posts. The overall correlation obtained across the platforms have been 0.19, which suggests that engagement is likely to increase at a very slow rate with an increase in post activity across the platform, irrespective of the content type. However, the individual platform correlation suggests that engagement over Instagram can be increased by increasing the activity level in a very aggressive manner, as the correlation obtained for the platform was 0.61. It is followed by Facebook with correlation estimates of 0.44, suggesting that a selective increase in content type can increase engagement. These findings are in line with earlier research, which suggested that activity directly impacts engagement in general (Moran et al., 2020). That can also be observed with 'Video' content over Twitter, which received a very low share of content in comparison to other types but generated a higher volume of engagement. The theme efficiency analysis suggests that not all content themes perform identically across the platforms. 'Entertainment' content theme has the highest average efficiency for Facebook with 875, followed by 'Transformational' with 633. The lowest efficiency was obtained for 'Transactional' with an efficiency rating of 135. As a platform, Instagram has the highest average efficiency across the themes compared to other platforms. 'Transactional' content has the lowest efficiency for Instagram as same as Facebook. Twitter (now X) is the only platform which has the highest average efficiency for 'Transactional' content with an efficiency rating of 378. In terms of platform, YouTube is the least efficient platform, with all the forms of content themes having lesser efficiency for given content themes compared to other platforms. The least performing content theme is 'Entertainment' over YouTube, whereas 'Informational' has the highest efficiency. The results obtained from the Kruskal–Wallis analysis suggest that Instagram is the only platform where the publisher can directly influence engagement in a positive manner by increasing activity level irrespective of the content type and theme. All the other platforms have a significant difference in engagement volume compared to the content types. That precisely means the content types and themes found to be having a higher level of efficiency must be given more consideration. The efficiency of a content type can be highly influenced by the level of activity it receives. That means if a content type or theme fails to maintain the engagement volume after increasing the level of activity, it is likely to become less efficient. The finding with YouTube suggests that 70 percent of its engagement comes from entertainment videos, but it also has the lowest efficiency. Here, the problem arises as other forms of content themes are likely to cover only 30 percent of total engagement. The following are optimized content structures for the platform starting Facebook, the obtained optimized structure for the $Target\ Interaction_{Share} = Structure\ \{Ty=5,\ PA=3,\ UI=3,\ TA=3,\ Th_{Transformational}\}$ similarly for Instagram the $Target\ Interaction_{Comment} = Structure\ \{Ty=5,\ PA=2,\ UI=4,\ TA=3,\ Th_{Entertainment}\}$ For Twitter the $Target\ Interaction_{Like} = Structure\ \{Ty=5,\ PA=2,\ UI=3,\ TA=3,\ Th_{Entertainment}\}$ and for YouTube the $Target\ Interaction_{Share} = Structure\ \{Ty=5,\ PA=2,\ UI=4,\ TA=3,\ Th\ Informational\}$.

6. PRACTICAL IMPLICATIONS

Through analysis of more than 7,000 posts from Indian state tourism pages, the study reveals the effects of various forms of content organization on engagement for four major social media platforms, which include Facebook, Instagram, Twitter (currently known as X), and YouTube. It should be noted that this paper considers the behavior of real-world content instead of making hypothetical assumptions. From the results obtained, video posts have proven to be more efficient on Facebook and Twitter when compared to posts containing text and images only. This is indeed predictable based on how users tend to view content in both social media networks. The case of Instagram is a bit different, where posts containing various forms of content achieve an equally distributed level of performance, although relatively better than others. Furthermore, the study employs Content Structural Efficiency (CSE), which is an extension of the work by Tafesse and Wien (2017) and Laskey et al. (1989). The method of content classification in this study has been employed in conformity with the recommendation made by Anandarajan et al. (2019). This means that the techniques used were a combination of inductive and deductive techniques. The intercoder reliabilities obtained varied between 0.71 and 0.82. In real life, the study results reveal that firms involved in the tourism sector must not concentrate solely on a particular kind of content. Rather, they must consider the behavioral pattern of the platform and the audience's expectations. Moreover, the framework employed in this research could serve as a helpful guide in creating and analyzing social media content.

7. LIMITATIONS

However, there are certain limitations that should be considered while interpreting these outcomes. To begin with, there is a specific period for which the data used in this current research was gathered. As far as tourism is concerned, the degree of tourist activity varies based on seasons, campaigns, and even tourism cycles. Hence, there may have been a possibility of ignoring some variations. An additional aspect relates to the range of information analyzed. The research focuses exclusively on the data related to the websites run by the tourism ministries of Indian states. While this was a conscious choice made in order to ensure the uniformity of results, it also implies that the findings can be regarded as being characteristic for the practices employed within the governmental sector of communication. Further research should take into consideration two aspects. Firstly, it should consider a longer period of time analysis so that seasonal and event-related variations may be accounted for more precisely. Secondly, it should include information about private sector companies and foreign tourism boards' statistics as well. Comparison of the two sets of data would allow us to understand how consistent our findings were across different scenarios.

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