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Empirical Research Article

Social Media Marketing Strategies for Tourism Destinations: Effects of Linguistic Features and Content Types

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Abstract

This study explored the relationship between post types and linguistic characteristics in marketer-generated content and social media engagement to find the optimized content to enhance social media engagement level. Post data of 23,588 marketer-generated content were collected from 50 states' destination marketing organization Facebook pages in the United States. The collected data were analyzed by employing social media analytics, linguistic analysis, multivariate analysis of variance, and discriminant analysis. The results showed that there are significant differences in both engagement indicators and linguistic scores among the three post types. Based on research findings, this research not only provided researchers with theoretical implications but also suggested practitioners the most effective content designs for travel destination marketing in Facebook.

Keywords

social media engagement; Language Expectancy Theory; linguistic feature; Facebook; destination marketing organization

1. Introduction

Social media has become an undisputed marketing channel for tourism destination marketing (Uşaklı, Koç, & Sönmez, 2017). Unlike a traditional marketing channel, social media sites provide marketers with various functions that allow marketers to attach images, videos, hyperlinks, schedules and to share with many social media users. These functions enable marketers to attract potential tourists to their places, thereby enhancing social media user relationships (Song, Park, & Park, 2021). For instance, Facebook possesses the largest number of users and communities by employing this development strategy (Facebook, 2021). Thus, the majority of destination marketing organizations (DMOs) have developed their Facebook brand pages and posted marketer-generated content (MGC) to engage potential travelers as well as page followers (Villamediana, Küster, & Vila, 2019). As the tourism industry relies heavily on marketing tactics with information such as brand awareness, image, or reviews, understanding antecedents of enhancing social media engagement is more important to implement successful social media marketing strategies.

For the needs, many researchers have examined content design elements or themes to increase user engagement behaviors (e.g., like, comment, share) and have provided theoretical or practical implications regarding strengthening user engagement for social media marketing (Edosomwan, Prakasan, Kouame, Watson, & Seymour, 2011; Zeng & Gerritsen, 2014). Factors investigated in existing literature are publishers, content types, topics, themes, time frames contained social media post data (e.g., Alboqami et al., 2015; Li & Xie, 2020; Mariani, Mura, & Di Felice, 2018; Song et al., 2021; Villamediana et al., 2019). For example, Alboqami et al. (2015) demonstrated the importance of using visual materials to enhance user engagement. Villamediana et al. (2019) claimed that different publication time frames differently affect user engagement. Song et al. (2021) analyzed the different effects of photo themes displayed in Facebook pages on facilitating social media user engagement levels. The most frequently examined by researchers was content type such as text message, photo, video, link, and so on. Many researchers (e.g., Alboqami et al., 2015; Song et al., 2021; Stepchenkova & Zhan, 2013) have provided a similar conclusion that visual materials are more effective to enhance user engagement levels than other types.

The influences of text messages in MGC on social media engagement have not received attention while the significant effects of visual materials (i.e., videos, photographs) on increasing user engagement behaviors in social media have been frequently explored in social media marketing research (e.g., Alboqami et al., 2015; Boley et al., 2013). Language or message which is a core component in social media communication is carefully crafted along with visual materials to positively affect the information receiver's attitude or behaviors (Burgoon, Jones, & Stewart, 1975; Byun & Jang, 2015). According to Language Expectancy Theory (LET), strategic use of linguistic features would increase the power of persuasiveness of the delivered messages (Burgoon, Denning, & Roberts, 2002). In other words, generating efficient and strategic messages in MGC means identifying or using optimal combinations of linguistic features in messages (e.g., length of the message, sentiment, analytic tone, authenticity), in which the tactics can enhance involvement and engagement of social media users in online communities. As MGCs generally consist of diverse types like text messages and

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visual materials, the roles of linguistic features as well as post types with visual materials in increasing engagement should be investigated.

This study examines the significance of linguistic characteristics in messages and post content types of MGCs on drawing social media engagement behaviors, including reaction, comment, and share for destination marketing with social media. This study reviews existing research articles and theories related to social media engagement and linguistic characteristics. DMO Facebook pages of 50 states in the US were targeted for data collection. Social media analytics and statistical analysis were employed to test the research questions proposed from the literature review. This study aims to provide theoretical insights related to the effects of MGC post types and linguistic features and valuable practical suggestions, including MGC design ideas to maximize social media engagement levels in DMO Facebook pages.

2. Literature Review

2.1 Social Media and User Engagement for Destination Marketing

Tourism innovation strategies have evolved with emerging information and communication technologies (ICTs) to make tourism management more effective and efficient (Li, Hu, Huang, & Duan, 2017). The integration of ICTs has tremendous influence on the improvement in traveler experiences and travel destination marketing practices (Gretzel, Sigala, Xiang, & Koo, 2015). The explosive growth of social media networks has changed the marketing media structure and the relationships between marketers and customers in all industries, and it is no exception to tourism marketing as a site where marketers and users co-create values (Femenia-Serra & Ivars-Baidal, 2021; Koo, Gretzel, Hunter, & Chung, 2015; Uşaklı et al., 2017). Users as well as marketers interactively produce digital content (i.e., marketer-generated content, user-generated content) and have conversations in cyberspace. Data in social media networks provide invaluable insights regarding marketing trends, themes, customer sentiment, e-WOM patterns, or brand awareness. Thus, one of the desired goals in social media marketing is to maintain reciprocal communication between marketers and users and enhance the relationship among all stakeholders in the social media community.

Engagement refers to the relationships or connections between customers and companies, including brands (Van Doorn et al., 2010), and has been considered a critical marketing tool to boost customer loyalty or trust (Van Asperen, de Rooij, & Dijkmans, 2018). Practitioners not only develop digital travel experiences in social media to engage more users but also gain insights into their social media marketing performance (Dewnarain, Ramkissoon, & Mavondo, 2019; Hays, Page, & Buhalis, 2013; Mariani et al., 2018). Social media engagement includes forwards of posted content to other fans' followers, so that ultimately the engagement itself can be considered one of the most desirable outcomes of social media marketing. Users have engaged in social media communities by reacting to social media posts or sharing their ideas related to interesting topics (Jansen, Zhang, Sobel, & Chowdury, 2009).

Social media engagement theory (SMET) describes the role of technology as the underlying platform to enhance social interactions among users. The technical features of social media platforms and their effect on social interactions among users to influence user engagement are explained in the theory (Di Gangi & Wasko, 2016). According to the SMET, user experiences generated from interactions among social media users and technical features of the social media platform are more likely to be related to users' engagement. In the light of the development of effective social media marketing content for marketing (Majid, Lopez, Megicks, & Lim, 2019), 'infotainment' is one of the critical factors that influence the effectiveness of social media marketing messages. It means that marketing messages in social media should contain elements to be relevant, valuable, interesting, or amusing to people and the well-designed messages regarding infotainment are more effective to create favorable behaviors of social media users. Based on the previous claims, one research question (RQ1) to explore major message elements (i.e., topics in text messages) in DMO Facebook pages is posed to better understand main themes in social media engagement marketing and to develop marketing implications:

- RQ1. What are the major topics contained in social media messages for travel destination marketing?

2.2 Cues to Enhance User Engagement in Facebook Brand Pages

Antecedents to facilitate social media engagement levels have been recently investigated in tourism research (e.g., Harrigan, Evers, Miles, & Daly, 2017; Song et al., 2021). In particular, researchers have paid attention to social media engagement in Facebook due to its popularity and multimedia features in designing MGC (e.g., Mariani et al., 2018; Pérez-Vega, Taheri, Farrington, & O'Gorman, 2018). Several studies noted that the social media marketing performance of Facebook brand pages varies and that engagement levels can be affected by different brand pages (Hays et al., 2013; Mariani et al., 2018; Park, Park, Park, & Back, 2020).

In existing discussion, it seems consistent that visual materials in MGC significantly affect increasing social media engagement scores such as the number of likes, comments, or shares. In particular, the number of reactions has been widely used instead of the number of likes in Facebook studies as one of the engagement behaviors because reactions include other emoji buttons (e.g., love or sad) as well as likes. Pictorial images of travel destinations play a critical role in engaging social media users as well as in creating projected images (Song et al., 2021; Stepchenkova & Zhan, 2013). Accordingly, the second research question (RQ2) to examine different effects by content types on increasing engagement levels is posed:

- RQ2: What types of MGC are the most effective to enhance engagement levels (reaction, comment, share) in DMO Facebook pages?

2.3 The Relationship Between Linguistic Features and Engagement

Strategic language usage has been found to influence consumers' attitudes toward the advertisement and the product (Krishna & Ahluwalia, 2008). The language used in effective advertising for destinations may influence travelers' attitudes and behavioral intentions (Byun & Jang, 2015). According to Language Expectancy Theory (LET), strategic linguistic uses can be significant predictors of positive behavioral changes (Burgoon et al., 1975). Language is a rule-governed system and consumers may develop expectations about the language or message strategies in response to persuasive attempts according to LET (Burgoon, 1995). LET helps to identify how the various features of any given message positively or negatively conform to macro-level expectations about what constitutes effective communication attempts (Burgoon et al., 2002). LET has often been applied to research investigating the effects of textual information (e.g., online reviews) on potential consumers (e.g., Jensen et al., 2013). For example, Parhankangas and Renko (2017) found that linguistic styles enhance the success of social crowdfunding campaigns.

From a LET perspective, social media managers should include words they believe are important and valuable to their destinations. Thus, a more favorable attitude or behavioral change (i.e., reservation) can be expected by posting carefully crafted posts. From a managerial perspective, it is important for service providers to understand consumer perceptions of all attributes associated with the price and to recognize unique features related to customers' willingness to pay. In this regard, a destination's features should be well highlighted in the postings by the social media managers to be attractive to potential tourists. Although several scholars have called for broadening the research scope through examining language features in various communication contexts (Averbeck & Miller, 2014; Burgoon et al., 2002; Burgoon, 1995), LET has not been frequently examined in social media marketing. This study responds to this call by extending the LET application to social media management in destination marketing organizations by examining the role of language in postings on engagement.

Messages in MGC deliver unique or attractive themes related to brands of Facebook fan pages. Researchers in other disciplines explored the effects of linguistic characteristics of social media content on engagement levels. Researchers (Leek, Houghton, & Canning, 2019) conducted a predictive analysis with Twitter data. The research paid attention to the psycholinguistic characteristics defined by the Linguistic Inquiry and Word Count (LIWC), such as anger, cognition, communication, anxiety, positive emotion, etc. Their studies concluded that the linguistic categories on tweets have significant influences in encouraging replies or retweets. Duncan, Chohan, and Ferreira (2019) used similar research approaches for text content analysis. The outcomes presented that the linguistic variables (tone, word count, frequency) are effective in enhancing user engagement behaviors in social media. According to the previous studies, it can be posed that linguistic components can be designed in different social media marketing content types. In addition, it can be expected that the linguistic characteristics are different between high and low engagement groups. The third research question (RQ3) is as follows:

- RQ3: What linguistic features (word count, analytic thinking, clout, authentic, emotional tone) are the most effective to enhance engagement levels (reaction, comment, share) in DMO Facebook pages?

3. Method

3.1 Data Collection

Researchers collected data of MGC published in 50 official state DMO Facebook pages of the United States (see Figure 1.). The hyperlinks to the official Facebook pages were found on the DMO's official websites. MGCs gathered were published for a year from November 1, 2016 to October 31, 2017. Netvizz on Facebook which is a Facebook data extraction tool was utilized for data collection. The dataset includes variables like content type, post link, post message, publication time, publisher, numbers of likes/comments/shares, etc.

In total, post data of 23,813 MGCs were collected. Researchers randomly extracted 10% of the initially collected samples and manually reviewed text messages in the 10% subset. The review confirmed that there is no irrelevant content in the dataset. This study examines the effects of three content types (photo, video, link) on changing engagement levels. Thus, other type posts such as event, note, status (0.94% of the initial dataset) were removed and the final data set for analysis contained 23,588 post data (photo: 10,094 + video: 2,608 + link: 10,886).

3.2 Data Analysis

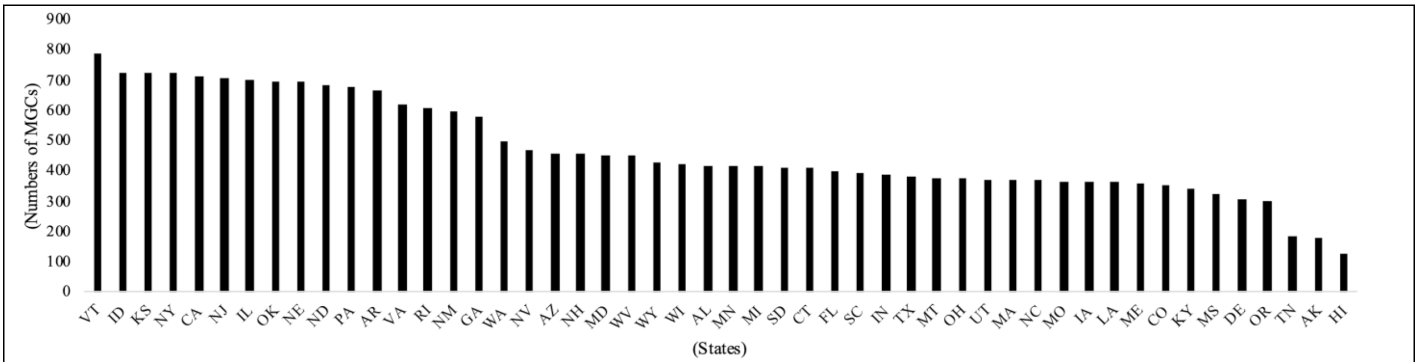
Data screening and frequent word analysis were conducted by using EXCEL and Voyant Tools to investigate RQ1. The linguistic content analysis was performed from the posts using Linguistic Inquiry and Word Count (LIWC), which are widely used language analysis software, by calculating values to quantify the linguistic characteristics. LIWC provides the Facebook posts on four different dimensions and its scale ranges are from zero (low) to 100 (high): *Analytical Thinking* (indicating if the posts are written in a formal, logical, or hierarchical way), *Clout* (indicating if the posts are written from the perspective of high expertise and are confident), *Authentic* (indicating if the posts are written with a more honest, personal, and disclosing text), and *Emotional Tone* (indicating if the posts are written more positive or upbeat way) (LIWC, 2021; Pennebaker, Booth, Boyd, & Francis, 2015). The scores for these four dimensions and word counts in the posts were included in the analyses.

Two statistical methods were employed to test the proposed research questions: a multivariate analysis of variance (MANOVA) and discriminant analysis. In particular, the MANOVA was conducted to investigate the effect of the post type on engagement indicators (RQ2). In addition, the discriminant analysis was employed to clarify the linguistic characteristics of the post contents that show high and low engagements (RQ3). SPSS 27.0 was used to conduct statistical analyses.

4. Results

4.1 Descriptive Analysis

The average number of MGCs published on each Facebook page was 417.76 during this data collection period. The DMO pages of Vermont (787), Idaho (725), and Kansas (724) were the top three most productive sites in posting MGCs on Facebook. In terms of the average of likes per MGC, the DMO pages of Hawaii (3,873.4), Montana (2,450.0), and Minnesota (2,128) had the largest numbers of likes per content. In terms of the average of comments per MGC, the DMO pages of Colorado (185.7), Hawaii (177.6), and Minnesota (143.8) received the most comments per content. In terms of the average of shares per MGC, the DMO pages of Minnesota (671.7), Michigan (661.4), and Florida (598.4) recorded the largest numbers of shares per content.



(N=23,588)

(Period: from November 1 2016 to October 31 2017)

Fig. 1. Numbers of MGCs per DMO Facebook page

Many MGCs contain text messages. Table 1 presents the top 30 words most frequently used in composing messages. The most frequent words were *visit* (2,226), *new* (2,154), and *photo* (2,056). It was notable that several words were related to seasons like *summer* (1,129), *fall* (1,039), and *winter* (999). Many DMO marketers promoted *national* (1,241), *park* (1,718), *festival* (972), and *adventure* (835).

The link-type MGCs (10,886 posts) occupied 46.2% of the dataset followed by the photo-type MGCs (10,094 posts; 42.8%) and the video-type MGCs (2,608 posts; 11.1%).

4.2 Descriptive Statistics for Linguistic Analysis Scores and Engagement

Table 2 shows descriptive statistics of five scores calculated by using Linguistic Analysis (i.e., *Word Count, Analytic Thinking, Clout, Authentic, Emotional Tone*) and three engagement indicators (i.e., *Reaction, Comment, Share*).

Table 1. Results of frequent word analysis

Rank	Word	Frequency	Rank	Word	Frequency	Rank	Word	Frequency
1	*visit*	2,226	11	*great*	1,209	21	*north*	900
2	*new*	2,154	12	*favorite*	1,190	22	*enjoy*	898
3	*photo*	2,056	13	*summer*	1,129	23	*like*	888
4	*weekend*	1,790	14	*fun*	1,058	24	*year*	864
5	*park*	1,718	15	*fall*	1,039	25	*beautiful*	844
6	*check*	1,666	16	*today*	1,030	26	*adventure*	835
7	*trip*	1,308	17	*winter*	999	27	*week*	810
8	*time*	1,304	18	*city*	987	28	*list*	808
9	*national*	1,241	19	*festival*	972	29	*experience*	800
10	*best*	1,238	20	*family*	910	30	*season*	792

Note. Several words that are not meaningful for this study were removed (e.g., *http*, *bit.ly*, *ðÿ*, *ow.ly*, *state*, *day*, *today*, *make*, etc.)

Table 2. Descriptive statistics for linguistic analysis scores and engagement indicators

Variable		N	Range	Mean	SD
Linguistic Score	Word Count	23588	389	26.75	17.80
	Analytic Thinking	23588	99	88.19	18.91
	Clout	23588	99	73.71	20.75
	Authentic	23588	99	42.95	34.83
	Emotional Tone	23588	99	67.45	37.85
Engagement	Reaction	23588	83344	589.95	1644.74
	Comment	23588	7133	34.52	136.55
	Share	23588	25050	130.66	561.24

4.3 Multivariate Analysis of Variance: Post Type and Engagement

One-way MANOVA examined the three engagement indicators (i.e., *Reaction, Comment, Share*) as dependent variables (DVs) and the post type (i.e., video, photo, link) as an independent variable (IV). The multivariate result was significant for types of post, $F(6, 47166) = 106.62$, $p < .001$; Wilk's $\lambda = 0.973$, $\eta_p^2 = .013$, indicating a difference in the level of engagement among three post types. As the MANOVA result is significant, a series of univariate ANOVAs were conducted as follow-up tests. The univariate *F*-tests showed that there was a statistically significant difference in the level of three engagement indicators based on types of post for *reaction*, $F(2, 23585) = 175.47$, $p < .001$, $\eta_p^2 = .015$, *comment*, $F(2, 23585) = 116.84$, $p < .001$, $\eta_p^2 = .01$, and *share*, $F(2, 23585) = 67.80$, $p < .001$, $\eta_p^2 = .006$ (see Table 3). As the univariate ANOVA follow-ups do not provide the specific mean difference, Bonferroni *post-hoc* test was employed to prevent alpha inflation at this level of the analysis.

Table 3. Significant *F*-tests for univariate follow up tests

DV		Sum of Squares	*df*	Mean Squares	*F*	*p*	η_p^2
Reaction	Type	935491726.744	2	467745863.372	175.466	< .001***	.015
	Residual	62871337153.309	23585	2665734.032			
Comment	Type	4314606.157	2	2157303.078	116.841	< .001***	.010
	Residual	435464647.158	23585	18463.627			
Share	Type	42468257.488	2	21234128.744	67.795	< .001***	.006
	Residual	7387126142.982	23585	313212.896			

Note. *: $p < .05$, ***: $p < .001$

Table 4 summarizes the significant findings and answers the RQ2 of this research. All mean differences were statistically significant except for the mean difference between video and photo for *reaction*. Specifically, Bonferroni *post-hoc* tests revealed that the mean of *reaction* was higher for photo (M = 778.244, SD = 2,040.269) and video (M = 758.697, SD = 1,938.963) than for link (M = 374.920, SD = 1,007.825). The mean of *comment* was higher for video (M = 67.713, SD = 195.737) than for either photo (M = 37.862, SD = 166.889) or link (M = 23.473, SD = 70.742). Also, the tests showed that the mean of *share* was higher for video (M = 248.097, SD = 958.538) than for either photo (M = 126.281, SD = 601.317) or link (M = 106.591, SD = 351.174).

Table 4. Significant mean difference test (Bonferroni)

DV	Type		Mean Difference	Std. Error	Sig.	95% CI	
						Lower	Upper
Reaction	Video	Photo	-19.55	35.86	1.000	-105.41	66.32
		Link	383.78	35.60	< .001***	298.56	469.00
	Photo	Link	403.32	22.56	< .001***	349.31	457.34
Comment	Video	Photo	29.85	2.99	< .001***	22.70	37.00
		Link	44.24	2.96	< .001***	37.15	51.33
	Photo	Link	14.39	1.88	< .001***	9.89	18.88
Share	Video	Photo	121.82	12.29	< .001***	92.38	151.25
		Link	141.51	12.20	< .001***	112.29	170.72
	Photo	Link	19.69	7.73	.033*	1.18	38.20

Note. *: $p < .05$, ***: $p < .001$

4.4 Discriminant Analysis: Linguistic Features and Engagement Groups

Although the result of the MANOVA identified the significant difference in the degree of each engagement indicator based on the post type, the characteristics of the linguistic scores increasing engagement indicators have not been clearly identified. In this regard, we assumed that engagement might be affected by the post's linguistic characteristics that are a combination of the five linguistic analysis scores. We attempted to investigate whether there is a significant difference in the linguistic features between high and low engagement groups or not. A discriminant analysis could be used to identify the optimal combination of the five linguistic analysis scores for increasing each engagement indicator. Before conducting a discriminant analysis, each engagement indicator was divided into two groups based on the median of each variable. Then, a discriminant analysis was conducted to test the research question (RQ3) that engagement indicators (i.e., *reaction, comment, shar*e) with high and low levels would differ significantly on a linear combination of five linguistic analysis scores (i.e., *Word Count, Analytic Thinking, Clout, Authentic, And Emotional Tone*).

Table 5 shows high and low groups' statistics for each engagement indicator. Table 6 indicates that there are statistically significant differences in the degrees of the five linguistic analysis scores between high and low groups. Regarding two groups of each engagement indicator, all linguistic scores of high groups are higher than those of low groups except for *Analytic Thinking*. That is, as the level of *Analytic Thinking* increases, the engagement level decreases.

Table 5. Group statistics of the Linguistic Analysis Scores

Engagement	Group	Linguistic Analysis Scores	M	SD	Valid N (%)
Reaction	Low	Word Count	26.02	16.41	11819 (50.1)
		Analytic Thinking	88.47	18.42	
		Clout	72.48	20.62	
		Authentic	41.05	34.51	
		Emotional Tone	66.05	35.18	
	High	Word Count	27.49	19.07	11769 (49.9)
		Analytic Thinking	87.91	19.39	
		Clout	74.94	20.80	
		Authentic	44.85	35.05	
		Emotional Tone	68.85	34.46	
Comment	Low	Word Count	25.81	16.10	12344 (52.3)
		Analytic Thinking	88.85	18.01	
		Clout	72.15	20.63	
		Authentic	42.39	34.73	
		Emotional Tone	66.55	35.07	
	High	Word Count	27.79	19.45	11244 (47.7)
		Analytic Thinking	87.47	19.83	
		Clout	75.42	20.74	
		Authentic	43.55	34.94	
		Emotional Tone	68.43	34.58	

Share	Low	Word Count	25.92	16.60	11818 (50.1)
		Analytic Thinking	89.02	17.58	
		Clout	72.59	20.57	
		Authentic	41.55	34.64	
		Emotional Tone	66.16	35.11	
	High	Word Count	27.59	18.89	11770 (49.9)
		Analytic Thinking	87.36	20.13	
		Clout	74.84	20.86	
		Authentic	44.35	34.97	
		Emotional Tone	68.74	34.53	
Total		Word Count	26.75	17.80	23588 (100)
		Analytic Thinking	88.19	18.91	
		Clout	73.71	20.75	
		Authentic	42.95	34.83	
		Emotional Tone	67.45	34.85	

Table 6. Tests of equality of group means

Engagement		**Wilks' l**	**F**	**df1**	**df2**	**Sig.**
Reaction	Word Count	.998	40.762	1	23586	< .001***
	Analytic Thinking	1.000	5.417	1	23586	.023*
	Clout	.996	82.909	1	23586	< .001***
	Authentic	.997	70.494	1	23586	< .001***
	Emotional Tone	.998	38.234	1	23586	< .001***
Comment	Word Count	.997	72.465	1	23586	< .001***
	Analytic Thinking	.999	31.408	1	23586	< .001***
	Clout	.994	147.250	1	23586	< .001***
	Authentic	1.000	6.560	1	23586	.010*
	Emotional Tone	.999	17.078	1	23586	< .001***
Share	Word Count	.998	52.344	1	23586	< .001***
	Analytic Thinking	.998	45.439	1	23586	< .001***
	Clout	.997	69.675	1	23586	< .001***
	Authentic	.998	38.133	1	23586	< .001***
	Emotional Tone	.999	32.385	1	23586	< .001***

Note. *: $p < .05$, ***: $p < .001$

Table 7 shows the discriminant loadings of each linguistic analysis score. Although a discriminant analysis provides standardized canonical discriminant function coefficients and structure matrix that shows discriminant loadings, in this study, discriminant loadings were used to evaluate the discriminant power of each independent variable as the discriminant powers of standardized canonical discriminant function coefficients might be lower due to multicollinearity. Generally, when a discriminant loading is larger than either .40 or -.40, the discriminant loading is regarded as statistically significant (Hair, Black, Babin, & Anderson, 2010). Based on this criterion, the level of reaction is influenced by *Clout*, *Authentic*, *Word Count*, and *Emotional Tone*. Regarding comment, *Clout* and *Word Count* have a statistically significant effect. The level of share is affected by *Clout*, *Word Count*, *Analytic Thinking* (negative direction), and *Authentic* (marginally significant). *Clout* has the largest influence on all three engagement indicators.

Table 7. Discriminant loadings

	Reaction	**Comment**	**Share**
Word Count	.416 (3)	.532 (2)	.467 (2)
Analytic Thinking	-.148 (5)	-.350 (3)	-.435 (3)
Clout	.593 (1)	.758 (1)	.538 (1)
Authentic	.547 (2)	.160 (5)	.398 (4)
Emotional Tone	.403 (4)	.258 (4)	.367 (5)
Wilks' l	.990	.989	.990
Chi-square	234.387	254.593	239.119
df	5	5	5
Sig.	< .001***	< .001***	< .001***

Note. Numbers in the parentheses indicate rankings, ***: $p < .001$

5. Discussion and Implications

5.1 Discussion

With the increasing importance of social media platforms' role in the context of tourism destination marketing, this study attempted to investigate DMOs' Facebook contents (i.e., MGCs) of 50 states in the United States. The descriptive analysis showed different content productivities (i.e., the numbers of MGCs posted) of each DMO. More importantly, the descriptive analysis results provided US DMO marketers with meaningful insights regarding RQ1. The most frequent words revealed indicated what topics DMO marketers focused on when promoting their own destination on Facebook. Frequently used words were related to tourism, such as *visit, photo, summer, fall, winter, national, park, festival,* and *adventure*. According to the suggestions of Majid et al. (2019), natural and seasonal resources are the most common infotainment topics practically used for travel destination marketing.

With regard to RQ2, the MANOVA result showed the significant effects of post types on users' engagement that are similar to the previous study findings (Park et al., 2020; Song et al., 2021; Stepchenkova & Zhan, 2013). The results showed slightly different effects of the post types on facilitating different engagement behaviors in US DMO Facebook pages. Specifically, link-type contents are significantly ineffective to increase the level of reactions (likes or emojis). To enhance the levels of comments and shares, video-type contents have a stronger effect followed by photo-type and link-type contents.

Aside from the effect of post type, this study also investigated differences in the linguistic characteristics between high and low engagement groups by performing a discriminant analysis. The discriminant analysis results provided useful insights for RQ3. The result showed statistically significant differences in linguistic analysis scores between high and low engagement groups. The high engagement groups showed higher linguistic analysis scores than the low engagement groups except for the *Analytic Thinking* score. In this regard, DMOs' social media managers should compose the contents casually to increase users' engagement. In addition, the result indicated that the *Clout* score in the contents plays a critical role in enhancing users' engagement (see Table 7). In other words, content showing a perspective of high expertise and confidence is encouraged to be posted on DMOs' Facebook pages to increase user engagement. All and all, the findings show that social media managers' content posting strategies ultimately attract different levels of engagement. That is, specific social media strategies can be developed based on DMOs' engagement goals.

5.2 Theoretical Implications

As this research used LET to examine if strategic linguistic choices are significant predictors of positive behavioral changes (Burgoon et al., 1975), linguistic dynamics used in a social media posting have been found as key elements of determining users' engagement. As mentioned in the literature review, LET explains that language is a rule-governed system and consumers may develop expectations about the language or message strategies in response to persuasive attempts (Burgoon, 1995). The findings of this study suggest that contents with higher language dimensions (*Clout*, *Authentic*, *Emotional Tone*) get higher engagement. As social media analytics using LET has not drawn much attention among scholars in social media marketing, this study contributes to the literature by providing a valuable tool (LIWC) and theoretical background for future social media research. The authors hope that social media marketing scholars keep discussing different views and opinions of social media research to expand LET in regard to smart tourism.

In addition, the MANOVA results are meaningful to support recent discussion related to different aspects of three engagement behaviors raised in recent studies (Kim & Yang, 2017; Song et al., 2021). The researchers argued that selecting a comment or share requires more effort while clicking a *like* (or emoji) would be the simplest way to maintain a relationship between the brand page and social media users. Therefore, exploring different antecedents and effects of post types and linguistic attributes to increase each engagement also supports the viewpoint about distinct characteristics of the three engagement behaviors.

5.3 Practical Implications

Social media marketers should contemplate content types and linguistic features when designing social media content. As utilizing photo- and video-types would increase users' engagement, marketers should consider preferentially using those types instead of the link-type. In addition, although the linguistic characteristics of each post type differ from each other, social media marketers should take care of the linguistic features of social media contents because the contents containing higher means of *Word Count*, *Clout*, *Authentic*, and *Emotional Tone* (except for *Analytic Thinking*) produce a higher level of users' engagement. Several studies (e.g., Seraj, Blackburn, & Pennebaker, 2021) claimed that social media users tend to use more personal and informal words when developing relationships, which means that low *Analytic Thinking* is more beneficial in enhancing engagement. That is, social media marketers should think about both post type and the linguistic characteristics of the contents when making their MGCs to increase users' engagement.

The results (see Table 2) presented that MGCs on the US DMO Facebook pages have been posted with the linguistic characteristics of high *Analytical Thinking* but low *Authentic* languages on average. The discriminant analysis and MANOVA outcomes claimed different styles of social media content to maximize the engagement scores of reactions, comments, and shares. The types and linguistic features of effective post designs to increase users' engagement are suggested in Table 8.

Table 8. Social media post design suggestions

	Design Suggestions	
Engagement	**Type**	**Linguistic Feature**
Reaction	Photo or Video	High Clout, Authentic, Word Count, and Emotional Tone
Comment	Video	High Clout and Word Count; Low Analytic Thinking
Share	Video	High Clout, Word Count, and Authentic; Low Analytic Thinking

Note. Regarding Share, the discriminant loading of the Authentic is marginally significant.

5.4 Limitations

Although this study provides meaningful implications to scholars and practitioners, this research is not free from study limitations. The first of which is that the LIWC does not divide *Emotional Tone* into positive and negative dimensions. As a result, using the *Emotional Tone* without dividing two dimensions might dilute the effects of *Emotional Tone* on users' engagement. Although marketing content generally contains positive emotion, it is necessary to consider the approaches to examine the influence of emotional tone on users' engagement precisely: 1) considering two dimensions of emotion separately or 2) using a positive emotional tone solely.

Even though this study identified the patterns and characteristics of MGCs, the study was limited to verify the optimal level of each linguistic score that increases users' engagement as much as possible. Moreover, some marketing content types, for example, between photo and link, could look confusing because link-type content can show a website image in a post. Thus, future research is recommended to use an experimental design to verify the optimal values of linguistic scores or content types. By doing so, it would be possible to suggest further fruitful practical suggestions to social media marketers.

Declaration of competing interests

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