Drivers of engagement with influencer posts about tourism destinations on Instagram: the role of number of followers, destination connection, and content sentiment

Abstract

Purpose

This study examines variations in engagement with influencer posts about tourism destinations on Instagram through the lens of the strength-of-weak-ties theory. It specifically analyzes the effects of influencer type (macro, micro, or nano), emotional ties to the destination (local versus travel influencers), and content sentiment (positive versus negative) on likes, comments, and overall engagement rates.

Design/methodology/approach

Web scraping and artificial intelligence techniques were employed to collect and analyze 34,175 Instagram posts from 11,357 influencers related to a specific tourism destination. Influencers were categorized by follower count and connection to the destination, while content sentiment was assessed using machine learning and deep learning techniques. Differences in engagement, likes, and comments rates were examined using a univariate generalized linear model.

Findings

The results indicate that influencers with fewer followers (nano-influencers) achieve a higher engagement rate. This effect is more pronounced when posts convey a negative sentiment, especially among travel influencers compared to local influencers. While this trend is observed for the like rate too, these interaction effects are not significant for the comments rate.

Originality/value

This study contributes to the literature by employing AI-based analysis and statistical modeling to examine Instagram engagement using data collected via web scraping. The findings provide actionable insights for destination marketing organizations (DMOs) to enable them to refine their strategies, enhance their promotional efforts, and increase destination visibility by identifying influencers with higher engagement through data-driven selection and targeted content curation.

Keywords

Social media influencers, artificial intelligence, web scraping, post sentiment, engagement.

1. Introduction

Enhancing user engagement on social media remains a central objective for tourism marketing professionals. Engagement increases brand visibility, purchase intention, and profitability (Venciute *et al.*, 2023). It also serves as a predictor of loyalty, visit intention, and customer retention by reflecting the depth of customer interactions with destinations (So *et al.,* 2020; So *et al.,* 2024). Engaged users process tourism information more thoroughly, develop stronger emotional bonds, and co-create content, thereby increasing the visibility and credibility of tourism messages (Lee et *al.,* 2021). Marketing professionals increasingly rely on social media influencers (SMIs) to reach target audiences (Xie-Carson *et al.*, 2023). Despite the continued growth of social media users, achieving high engagement levels remains challenging. Consequently, tourism organizations and destination marketing organizations (DMOs) must identify the drivers of engagement to maximize the impact of influencers online.

SMIs are frequently categorized by their number of followers (Agostino *et al.*, 2019). Prior research across various contexts generally indicates that engagement rates decrease as follower count increases (De Veirman *et al.*, 2017). Micro-influencers are recognized for their authenticity and targeted engagement (Xie-Carson *et al.*, 2023). However, the impact of SMIs based on territorial or destination connection remains less explored (Ingrassia *et al.*, 2022). Both tourists and local SMIs contribute to the co-creation of destination image (Gomez *et al.*, 2018), yet limited research addresses which group generates higher engagement (Blanco-Moreno *et al*., 2024a). Few studies analyze local experiences at a tourism destination through SMIs (Ingrassia *et al.*, 2022). Additionally, while previous studies suggest that post sentiment (positive vs. negative) may affect engagement level (Boot *et al.,* 2021), most tourism research has focused primarily on positive content (e.g., Blanco-Moreno *et al.*, 2024a).

The existing research on SMIs in tourism and hospitality can be categorized into three primary streams (see **Appendix 1**): (1) the relationship between SMIs and social media users, with a focus on information perception and interaction (Xie-Carson *et al.,* 2023); (2) the relationship between SMIs and DMOs, including marketing strategies and measurable outcomes (Femenia-Serra & Gretzel, 2022); and (3) the personal characteristics of SMIs that influence engagement (Xie-Carson *et al.*, 2023). This study extends the literature on influencer marketing in three ways. First, it examines the differences in engagement level among SMIs based on follower count within the context of tourism destinations. Second, it considers the role of destination connection by differentiating between local and travel influencers, both of whom contribute to destination image formation. Third, it assesses whether the content's sentiment moderates the influence of SMI type.

These contributions are rooted in the various emotional ties that SMIs establish with followers, such as the size of the SMI community, the influencer's connection to the destination, and the sentiment of the content. These ties can drive engagement (Li *et al.*, 2025). This study is grounded in the strength of weak ties theory (Granovetter, 1973), which posits that even weak ties facilitate access to new information, while strong ties foster deeper, more personal connections (Mariani *et al.*, 2023). Within this context, this research addresses three key questions:

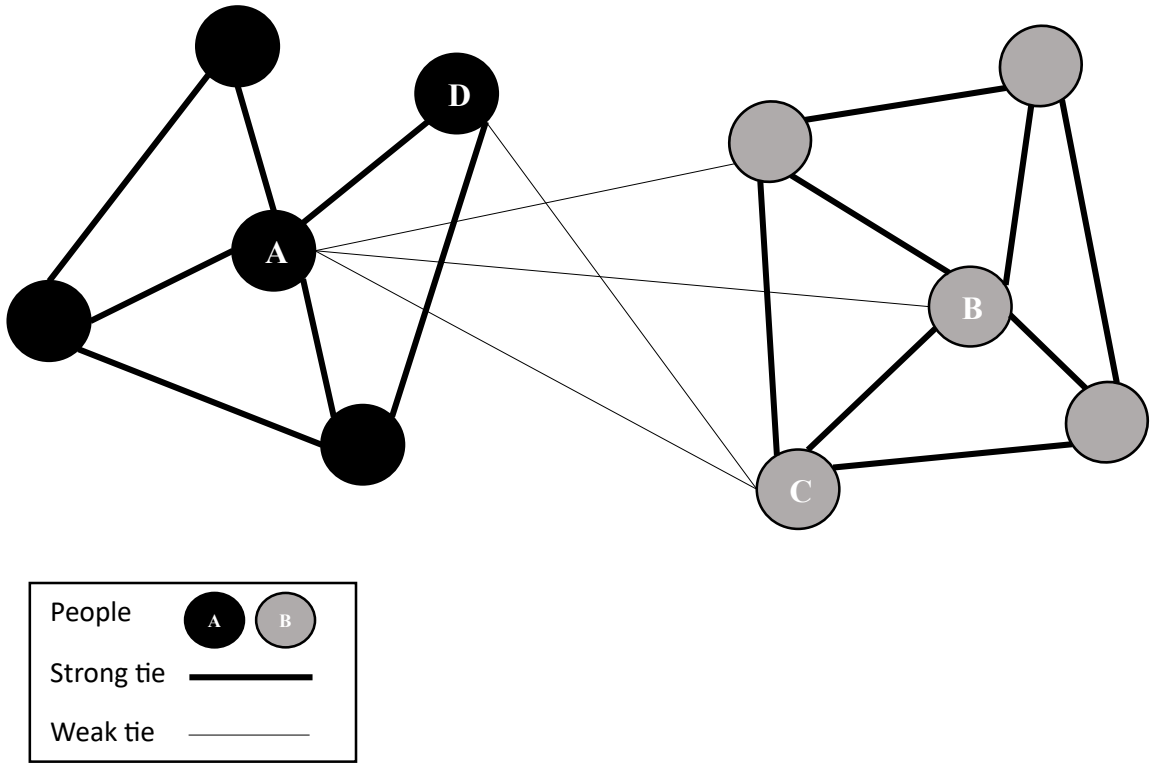
- What type of SMI should DMOs prioritize to maximize engagement? The number of an SMI's followers may influence the development of SMI-follower ties, thereby shaping engagement rates (Xu *et al.,* 2024).
- What is the role of the SMI's destination connection? Place identity strengthens social ties, suggesting that an influencer's local or tourist status may affect audience interaction (Ingrassia *et al.*, 2022).
- What is the role of the sentiment of the content? Followers may develop different emotional ties to SMIs depending on content sentiment (e.g., Boot *et al.*, 2021), eliciting stronger emotional reactions (e.g., engagement) when strong ties form.

This research focuses on Instagram, which has emerged as the primary platform for travel influencers and supports visual storytelling that shapes destination choice (Casaló *et al.*, 2020). With approximately 3 billion monthly active users and a significant volume of travel-related content (DataReportal, 2025), Instagram occupies a central role in digital tourism marketing. This study examines how engagement on Instagram varies by SMI type, destination connection, and content sentiment, as these factors may foster distinct emotional ties with followers. To address these questions, data was extracted from Instagram posts about a specific tourism destination, with posts classified by influencer type (nano, micro, or macro), connection to the destination (local or travel), sentiment (positive or negative). The findings offer insights into optimal influencer selection for maximizing engagement and inform marketing strategies by identifying influencer attributes that enhance engagement rates.

2. Theoretical background: The strength of weak ties theory, social influence & engagement

Humans develop social networks with both strong and weak ties, each serving distinct functions. Weak ties connect people to a broader network, helping them access diverse information and new opportunities. Strong ties provide deep, emotionally significant relationships and foster frequent interactions and strong emotional responses (Granovetter, 1973; Li *et al.*, 2025). Strong ties between nodes in the network exert a greater influence on an individuals' behavior. **Figure 1** represents this; the link between nodes A and B is a weak tie, while the link between nodes A and D is a strong tie.

Figure 1. Granovetter's strength of weak ties theory (1973).



Source: Own elaboration from Granovetter (1973)

Social media platforms such as Instagram illustrate how influencers build networks with followers, exhibiting varying tie strengths. Weak ties facilitate broad content dissemination (Himelboim & Golan, 2023). Engagement is conceptualized as a psychological state resulting from interactive and co-creative experiences with an actor or brand (So *et al.,* 2024). It encompasses cognitive, emotional, and behavioral actions that extend beyond passive content consumption and reflects the users' motivation. For influencers, engagement occurs when followers develop affective and relational bonds that motivate them to like, comment, or share posts, thereby signaling value co-creation and relationship strength. As these ties strengthen and the influencer becomes more akin to a real friend, follower engagement tends to increase (Wies *et al.,* 2023).

Consistent with the strength of weak ties theory (Granovetter, 1973), emotional ties serve as the mechanism through which relational closeness enhances the likelihood of active engagement. The existing literature shows that stronger emotional ties foster greater engagement by intensifying attention, empathy, and the willingness to interact with the content (Wies *et al.,* 2023). Specifically, emotional ties refer to the affective bonds followers develop toward (1) the influencer, (2) the destination, or (3) the content shared on social media.

These ties encompass feelings of familiarity, identification, trust, and perceived relational closeness, all of which shape how audiences attend to, interpret, and interact with social media posts. The theoretical foundations for emotional ties are found in social influence and media psychology, including parasocial relationships, where audiences form one-

sided but emotionally meaningful bonds with media figures (Horton & Wohl, 1956; Chung & Cho, 2017), and affective attachment processes that reinforce engagement and behavioral responses (Mariani *et al.,* 2023). At the influencer level, emotional ties manifest through parasocial interaction and perceived relational intimacy, which increase trust, credibility, and engagement intentions (Chung & Cho, 2017; Xie-Carson *et al., 2*023). At the destination level, emotional ties correspond with the place attachment literature, suggesting that identity, belonging, and affective connection strengthen the responses to destination-related content (Han & Chen, 2022). At the content level, emotional ties are shaped by the emotional tone or sentiment of the post, with emotionally charged content, particularly negative content, eliciting stronger cognitive and affective reactions (Boot *et al.,* 2021). Across these three dimensions, emotional ties intensify user engagement behaviors such as liking, commenting, and sharing.

In summary, this study applies the strength of weak ties framework (Granovetter, 1973) to explain how varying engagement rates within tourism-related content on Instagram are influenced by the emotional connections that SMIs establish with their followers (Chung *et al.,* 2023).

3. Hypothesis development

3.1. Emotional ties with the influencer: The effect of SMI type on engagement

Followers develop emotional ties with influencers through perceived relational closeness, authenticity, and personal connection. The strength of weak ties theory (Granovetter, 1973) posits that network size and intimacy determine the strength of relational bonds: smaller, more personal networks foster stronger affective ties that intensify trust, attention, and interaction (Xu *et al.,* 2024). Nano-influencers generally maintain closer, more reciprocal communication with their followers, which enhances parasocial intimacy and perceived relatability (Chung & Cho, 2017; Wies *et al.,* 2023). These emotional ties increase the likelihood of engagement with influencer content, as followers are more likely to connect and respond to individuals they perceive as authentic.

In tourism, SMIs act as opinion leaders whose influence stems not only from their reach but also from the emotional bonds they form with their audiences (Femenia-Serra & Gretzel, 2020; Xie-Carson *et al.,* 2023). Prior research consistently shows that as influencer follower count increases, engagement tends to decrease due to reduced intimacy, perceived exclusivity, and personalized communication (De Veirman *et al.,* 2017; Tafesse & Wood, 2021). Although larger influencers may enjoy high visibility, their weaker ties with their followers limit affective resonance and reduce interactive responses (Borges-Tiago *et al., 2*023).

Thus, the number of followers is employed in this study as a behavioral proxy for tie strength in social-media relationships. Granovetter (1973) defines strong ties by frequent interaction, reciprocity, intimacy, and emotional closeness, while weak ties are marked by limited contact and shallower relationships. In influencer contexts, audience size constrains the extent of interpersonal communication that an influencer can maintain. Influencers with smaller followings are more likely to engage in reciprocal, personalized exchanges, which fosters stronger parasocial intimacy and relational closeness (Chung & Cho, 2017; Wies *et al.,* 2023), thereby increasing engagement with destination content (Lee & Lee, 2017). In contrast, as follower count rises, communication shifts to a one-to-

many model that is less personalized and less reciprocal, reflecting the characteristics of weak ties (Tafesse & Wood, 2021; Borges-Tiago *et al.,* 2023). Thus, follower count serves as a theoretically grounded indicator of potential emotional closeness and supports its use in predicting engagement behavior.

Given that strong emotional ties foster deeper interaction, content posted by influencers with fewer followers is expected to generate higher engagement across all interaction types. Stronger emotional ties are also anticipated to result in higher likes and comments rates, which represent varying levels of user effort. Likes indicate low-effort agreement, while comments require cognitive elaboration and emotional involvement (Hauser *et al.,* 2022). Accordingly, the following hypothesis is proposed:

> **H1:** The smaller the number of followers an influencer has, the higher the likes rate (H1a), comments rate (H1b), and engagement rate (H1c) on their posts.

3.2. Emotional ties with the destination: The role of local influencers vs. travel influencers

Emotional ties may also arise from the influencer's relationship with the destination. Place attachment theory indicates that feelings of familiarity, identity, and belonging enhance affective responses toward place-related stimuli (Han & Chen, 2022). In this context, a distinction is made between travel influencers (tourists posting during short-term visits) and local influencers (residents consistently posting from their habitual location) (Ingrassia e*t al.,* 2022). Local influencers act as community insiders possessing contextual knowledge, cultural familiarity, and lived experience within the destination. This insider status enhances authenticity, credibility, and perceived congruence between the influencer and the place, thereby strengthening the followers' emotional ties with the destination (Belanche *et al.,* 2021; Andrade-Cunha *et al., 2*025). In contrast, travel influencers, while providing novelty and exploration, generally do not convey the same depth of contextual identity or attachment, resulting in weaker place-based emotional responses.

Additionally, local influencers frequently utilize richer, contextually grounded storytelling that resonates with residents and culturally motivated tourists, thereby reinforcing emotional ties and identification with the destination (Andrade-Cunha *et al., 2*025; Rasel *et al.,* 2025). These emotional ties foster stronger obligations to support, interact with, and endorse local content (Renton & Simmonds, 2017). Conversely, travel influencers, despite their broader reach, tend to provide more generic and less identity-embedded representations of the place, which elicit weaker engagement (Lin & Xu, 2017).

Local influencers are therefore expected to amplify the mechanism proposed in **H1**. By fostering stronger emotional and identity-based ties with followers through shared context, community belonging, and credibility, the positive effect of having fewer followers (stronger influencer–follower ties) is anticipated to be even more pronounced for local influencers. Accordingly, the following hypothesis is proposed:

> **H2:** The effects proposed in a) H1a, b) H1b, and c) H1c are stronger for local (versus travel) influencers.

3.3. Emotional ties with the content of the post: The role of positive vs. negative sentiment of the content

Emotional ties may also originate from the emotional tone of the content itself. Media psychology research demonstrates that emotionally charged content elicits stronger cognitive and affective reactions, thereby increasing engagement behaviors such as liking and commenting (Boot *et al.,* 2021). Substantial evidence suggests that negative posts, such as expressions of dissatisfaction, critique, or concern, elicit more intense emotional responses than positive content, a phenomenon attributed to the well-established negativity bias (Nigmatullina & Rodossky, 2022). Negative messages attract greater attention, evoke empathy, and stimulate emotional contagion, prompting users to mirror the influencer's emotions and interact more with the content (Yoo *et al.,* 2024).

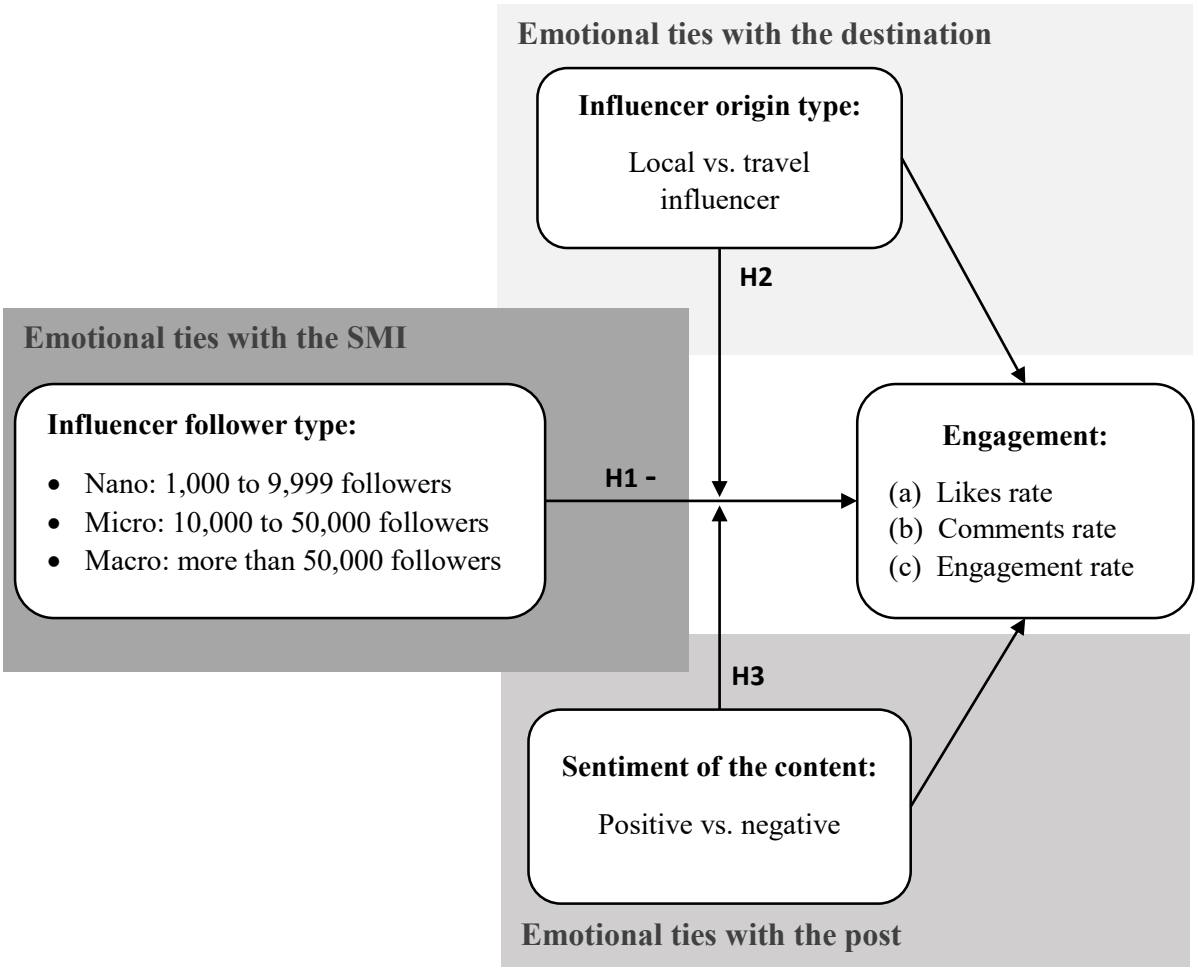
Within influencer contexts, negative sentiment can enhance perceptions of authenticity by humanizing the influencer and revealing vulnerability and genuine experiences, thereby deepening parasocial ties and follower identification (Ganguly, 2025). Research also indicates that negative UGC increases social interaction and debate, further amplifying engagement (Singgalen, 2024). In tourism, narratives about travel challenges or unexpected issues often evoke solidarity and support from followers, reinforcing emotional ties and strengthening the social ties between the influencer and their audience (Ganguly, 2025).

Consistent with the strength of weak ties theory, emotionally intense negative content strengthens affective connections, particularly when followers already maintain strong ties with influencers in smaller communities. Consequently, negative sentiment is expected to magnify the effect proposed in **H1**, resulting in higher engagement for posts expressing negative rather than positive emotions. The following hypothesis is therefore proposed:

> **H3:** The effects proposed in a) H1a, b) H1b, and c) H1c are stronger for negative-sentiment posts (versus positive-sentiment posts).

The conceptual model, including all proposed hypotheses, is presented in **Figure 2**.

Figure 2. Research model



4. Methodology

To examine the effect of influencer type on engagement, this study employs a multi-method approach integrating machine learning (ML) and deep learning (DL) techniques to analyze Instagram images, texts, and metadata. Instagram provides rich geotagged UGC related to hospitality (such as wineries and restaurants) and cultural attractions (such as museums, monuments), enabling the capture of authentic visitor interactions in the destination.

Only publicly available profiles were monitored, and all user identifiers were anonymized to ensure privacy and compliance with ethical research practices (Salvador-Almela *et al.*, 2025). Images containing identifiable individuals were blurred. The remainder of this section summarizes the artificial intelligence (AI) procedures, describes the research context, and outlines the data extraction and classification steps, following the procedure established by Blanco-Moreno *et al.* (2024a).

4.1. Literature review for methodology in AI

AI applications in tourism research have expanded considerably, particularly for analyzing UGC. Recent studies demonstrate the effectiveness of machine learning (ML) and natural language processing (NLP) for extracting sentiment, classifying text, and

analyzing tourist experiences (Zhang *et al.,* 2023). These methods enable researchers to quantify satisfaction, emotions, and destination image directly from social media data.

Simultaneously, deep learning (DL) techniques, particularly convolutional neural networks, have become central in tourism analytics for processing unstructured visual content, detecting emotions, and classifying image attributes (Blanco-Moreno *et al.,* 2024a). Their ability to interpret complex visual cues has enhanced research on tourist behavior, place perception, and online engagement.

Consistent with this stream of research, the present integrates ML-based sentiment analysis for textual data and DL-based emotion and feature recognition for visual data. This multimodal approach reflects the current methodological trends emphasizing the joint interpretation of images, text, and metadata in UGC-based tourism studies (Mariani *et al.,* 2023).

4.2. Data extraction

Web scraping, a widely adopted technique in marketing and tourism, was employed for the data extraction due to its capacity for automated, structured, and rapid collection from Instagram (Yu & Egger, 2021). This approach also ensures compliance with European Data Protection Law and facilitates anonymous data collection (Hauer, 2022).

This study focuses on León (Spain), an inland cultural and gastronomic destination along the Camino de Santiago, designated as a UNESCO World Heritage Site since 1993 (see **Appendix 2** for more information). The city primarily attracts cultural, gastronomic, and heritage-oriented visitors, many of whom travel for short stays and exhibit relatively homogeneous motivations centered on authenticity, local identity, and historical heritage. This homogeneity reduces confounding factors and provides a coherent context for examining how influencer type, destination connection, and post sentiment shape engagement patterns. Despite its size, León demonstrates high Instagram activity, particularly related to cultural and food content, making it a suitable setting for analyzing engagement with influencer posts.

To identify relevant posts about the destination, 245 official locations were used as data sources (Instagram, 2023). Using Phantom Buster software (Phantom Buster, 2023), 139,273 Instagram posts from 43,400 Instagram users over 13 years (2010–2022), including photos, texts, and metadata, were extracted, filtered, and analyzed. This process is summarized in **Figure 3**. Images were then downloaded using the Tab Save extension in Google Chrome (Chrome, 2023). AI was applied to analyze the research variables: ML assessed text sentiment, while DL identified the emotions in photos. The dataset enabled the distinguishing of influencers based on their follower and following counts, excluding non-influencers. **Figure 4** shows an example of the post data downloaded from Instagram. Additionally, local and travel influencers were distinguished based on the number of posts and the duration of posting about the destination. Specifically, the following methods were used: (1) DL analysis of visual content to extract emotions from the images, (2) ML analysis of the textual content to determine sentiment and engagement-related text variables, and (3) metadata analysis to classify influencers as travel or local. Ultimately, 34,175 posts from 11,357 influencers of both types were analyzed using a multi-method approach.

309 **Figure 3.** Data mining process using an artificial intelligence multi-methods approach

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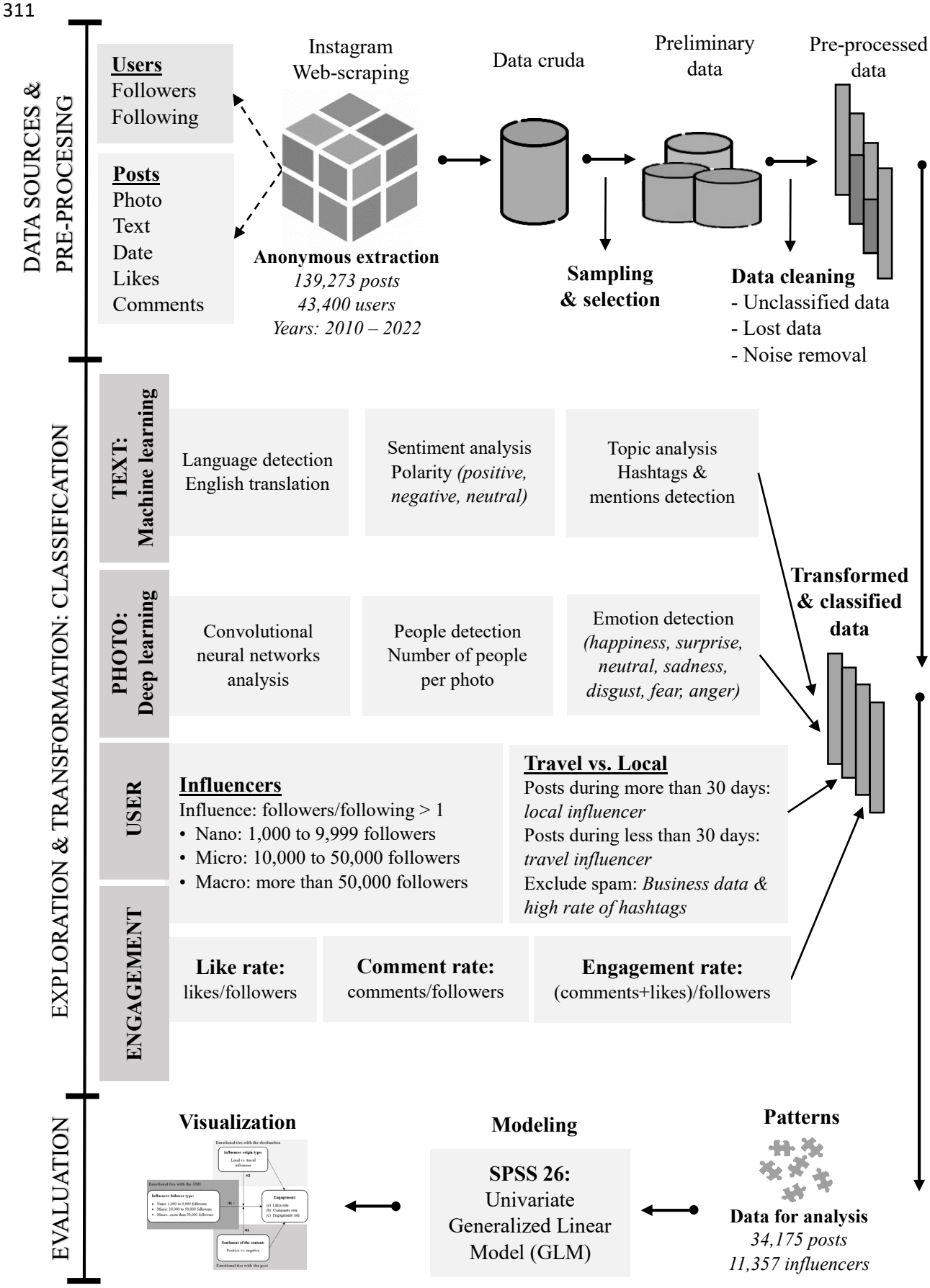
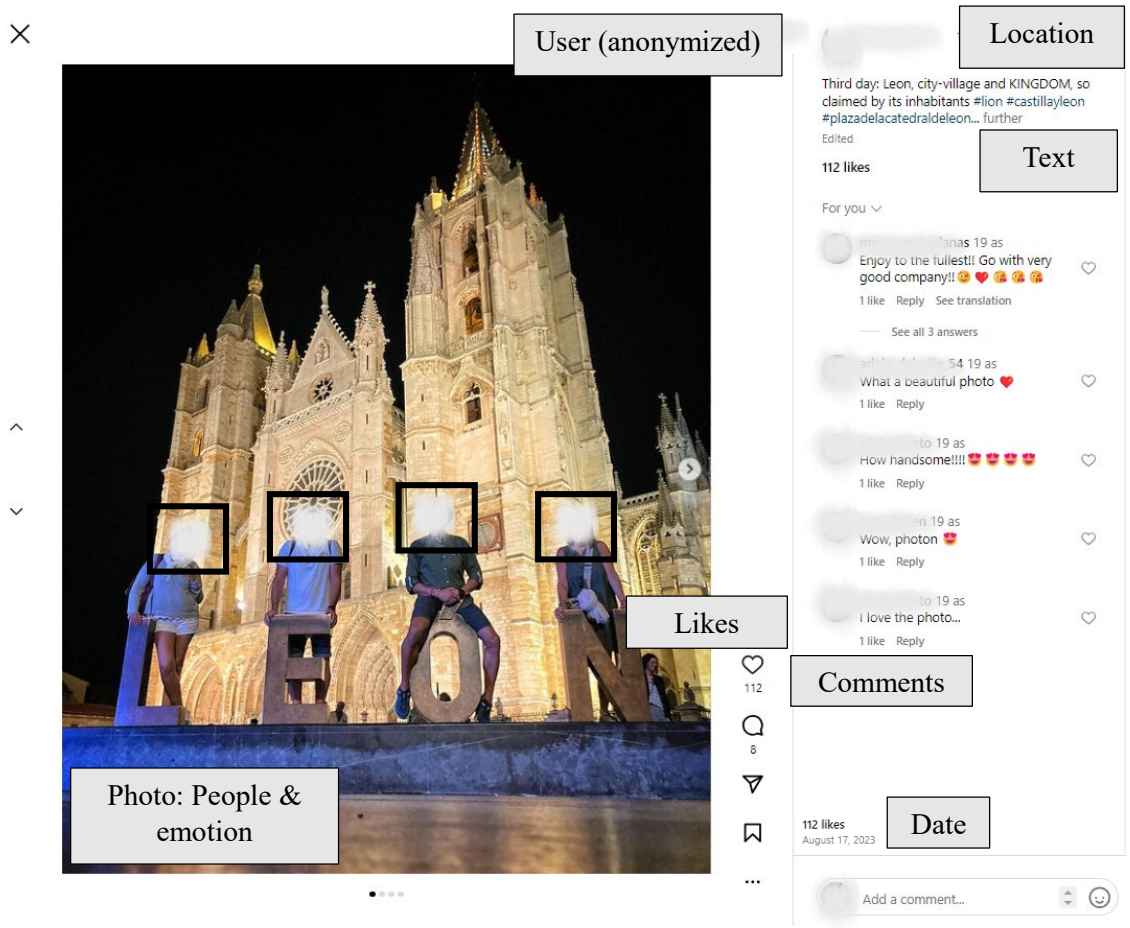

DATA SOURCES & PRE-PROCESING
Users
Followers
Following
Posts
Photo
Text
Date
Likes
Comments
Instagram
Web-scraping
Anonymous extraction
139,273 posts
43,400 users
Years: 2010 – 2022
Data cruda
Sampling & selection
Preliminary data
Data cleaning
- Unclassified data
- Lost data
- Noise removal
Pre-processed data
EXPLORATION & TRANSFORMATION: CLASSIFICATION
TEXT: Machine learning
Language detection
English translation
Sentiment analysis
Polarity (positive, negative, neutral)
Topic analysis
Hashtags & mentions detection
PHOTO: Deep learning
Convolutional neural networks analysis
People detection
Number of people per photo
Emotion detection
(happiness, surprise, neutral, sadness, disgust, fear, anger)
Transformed & classified data
USER
Influencers
Influence: followers/following > 1
• Nano: 1,000 to 9,999 followers
• Micro: 10,000 to 50,000 followers
• Macro: more than 50,000 followers
Travel vs. Local
Posts during more than 30 days: local influencer
Posts during less than 30 days: travel influencer
Exclude spam: Business data & high rate of hashtags
ENGAGEMENT
Like rate: likes/followers
Comment rate: comments/followers
Engagement rate: (comments+likes)/followers
EVALUATION
Visualization
Modeling
SPSS 26: Univariate Generalized Linear Model (GLM)
Patterns
Data for analysis
34,175 posts
11,357 influencers

Figure 4. Example of the post data downloaded from Instagram



Source: Instagram (2023c)

4.3. Classification of variables

First, after obtaining a clean database, users were classified based on their influence rate defined as the ratio of followers to those following (Blanco-Moreno *et al.*, 2024a). In line with previous research (Tafesse & Wood, 2021), users with more followers than those they were following were identified as influencers and categorized as nano- (1K–9.9K), micro- (10K–50K), and macro-influencers (>50K) respectively.

Following Gunter and Önder (2021), the distinction between travel and local influencers was determined by behavioral posting patterns rather than geotag presence, as geotags are inconsistently available across Instagram posts. In big social media datasets, posting duration and frequency serve as reliable proxies for differentiating residents from visitors when the geolocation data is incomplete. Accordingly, a three-step classification was implemented. First, users posting at the destination for more than 30 consecutive days were categorized as local influencers, while those posting for fewer than 30 consecutive days were classified as travel influencers. Second, to refine the classification over a 13-year dataset, users with fewer than 30 total posts about the destination were considered travel influencers, and those with more than 30 posts were labeled as local influencers. Third, text analysis was used to remove commercial accounts containing email addresses, phone numbers, or excessive hashtags. This triple-filtering approach aligns with

established big-data tourism methods and reduces misclassification when geotags are inconsistently available.

Text analysis was conducted using ML-based sentiment polarity (NLTK, 2023), producing normalized scores from –1 (negative) to +1 (positive). Image analysis employed DL models (DeepFace CNN) integrating VGG-Face and FaceNet, achieving reliability levels above 97% (Serengil, 2023). Emotion outputs were validated through Azure Computer Vision, reaching 96.5% agreement (Microsoft Azure, 2025). The multimodal sentiment variable was calculated by summing the text polarity and photo emotion scores; values below zero were coded as negative, and values above zero as positive.

The final step before the statistical analysis involved calculating the dependent variables. Three rates were computed: the likes rate (likes/followers), comments rate (comments/followers), and engagement rate ([comments + likes]/followers). Consistent with prior hospitality and tourism research, engagement is operationalized through observable interaction metrics that capture varying levels of user effort and emotional investment (Hauser *et al., 2*022). Likes rate represents low-effort, affective responses such as agreement or appreciation. The comments rate reflects higher-effort cognitive and emotional involvement, as comments require elaboration and intentional participation. Engagement rate, defined as the sum of likes and comments relative to the number of followers, provides a standardized measure that accounts for influencer audience size and is widely used in social media analytics research. These indicators enable the assessment of engagement as a behavioral manifestation of the emotional ties between influencers and their audiences. These measures, which utilize follower count, are widely accepted in the academic literature (Hauser *et al.*, 2022; Yu *et al.*, 2024). Additionally, comments and likes are used instead of other metrics, such as "sharing," because they are available on Instagram (Li & Xie, 2020). The structure and classification of the entire database, obtained after these steps, are presented in **Table 1**.

Table 1. Classification of the variables

Variable	Measure	Type	Technique	Author
Engagement rate	$\frac{\text{Likes + Comments}}{\text{Followers}}$	Continuous	Web scraping	Hauser *et al.* (2022); Yu *et al.* (2024)
Likes rate	$\frac{\text{Likes}}{\text{Followers}}$	Continuous	Web scraping	Hauser *et al.* (2022); Yu *et al.* (2024)
Comments rate	$\frac{\text{Comments}}{\text{Followers}}$	Continuous	Web scraping	Hauser *et al.* (2022); Yu *et al.* (2024)
Post sentiment	Polarity (between -1 and 1)	Continuous	Web scraping & ML	Bhatt and Pickering (2023); Bai *et al.* (2025)
	Emotion (between -1 and 1)	Continuous	Web scraping & DL	Blanco-Moreno *et al*. (2024a); Bai *et al.* (2025)
	0=Negative (polarity + emotion < 0) 1=Positive (polarity + emotion > 0)	Dichotomous	Web scraping & ML & DL	Developed in this study

Influencer type	By type of link with the destination	0=Local 1=Travel	Dichotomous	Web scraping	Gomez *et al.* (2018); Gunter and Önder (2021)
	By followers	Nano: 1,000 to 9,999 followers	Categorical	Web scraping	Xie-Carson *et al.* (2023)
		Micro: 10,000 to 50,000 followers			
		Macro: more than 50,000 followers			
Influence	$\frac{\text{Followers}}{\text{Following}}$	>1 → Influencer = <1 → Non-influencer	Dichotomous	Web scraping	Tafesse and Wood (2021)

To ensure methodological rigor and conceptual alignment, **Table 2** shows the purpose and justification of each data mining, ML, and DL technique employed in this research.

Table 2. Alignment of AI and data mining methods with this research

Method & tool	Purpose	Justification
DeepFace (Emotion Detection)	Identify dominant facial emotion (happy, neutral, etc.)	CNN-based emotion detection is standard in social media and tourism research (Serengil, 2023). Validated against the Azure Face API.
Custom bi-LSTM Sentiment Classifier	Analyze sentiment polarity in post captions.	LSTM networks excel at sequence learning for text polarity. Cross-validated with Azure NLP (Yu & Cheng, 2025).

As previously described, the final analysis database was comprised of 34,175 posts shared by 11,357 influencers. All groups considered in this research (based on influencer type, post sentiment, and emotional connection to the destination) were well-represented, as shown in **Table 3**.

Table 3. Sample classification

Construct	Classification	Number of posts
Influencer type (followers)	Nano	28,972
	Micro	4,630
	Macro	573
Post sentiment	Positive	23,676
	Negative	10,499
Link to the destination	Travel	19,888
	Local	14,287
	Total posts:	34,175

5. Results

Table 4 presents the descriptive statistics for likes rate, comments rate, and overall engagement rate, disaggregated by influencer type, sentiment polarity, and destination link. To facilitate interpretation, the main observed patterns are summarized as follows. The data confirms that nano-influencers achieve the highest engagement rate (M=4.726),

with engagement increasing further for negative sentiment posts (M=5.193) compared to positive ones (M=4.509), and for travel (M=4.921) rather than for local influencers (M=4.419). The likes rate follows a similar pattern, with nano-influencers showing the highest mean likes rate (M = 4.512), which is higher for negative posts (M=4.977) than for positive posts (4.296), and for travel influencers (M=4.687) than for local influencers (M=4.237). In contrast, macro-influencers consistently register the lowest engagement rate (M=1.136) and likes rate (M=1.072). Comments rate remains low across all groups, with only marginal variation (e.g., nano-influencers: 0.214; macro-influencers: 0.064).

Table 4. Mean and standard deviation (SD) values of the dependent variables: likes, comments, and engagement rates.

Influencer type	Rate	Total rate	Sentiment		Origin	
			Positive	Negative	Local	Travel
Nano	Likes	4.512 *(SD=5.247)*	4.296 *(SD=5.137)*	4.977 *(SD=5.446)*	4.237 *(SD=4.434)*	4.687 *(SD=5.696)*
	Comments	0.214 *(SD=0.918)*	0.212 *(SD=0.937)*	0.217 *(SD=0.876)*	0.181 *(SD=0.506)*	0.234 *(SD=1.102)*
	Engagement	4.726 *(SD=5.546)*	4.509 *(SD=5.439)*	5.193 *(SD=5.742)*	4.419 *(SD=4.684)*	4.921 *(SD=6.021)*
Micro	Likes	1.540 *(SD=1.959)*	1.497 *(SD=1.775)*	1.674 *(SD=2.444)*	1.251 *(SD=1.297)*	2.008 *(SD=2.642)*
	Comments	0.061 *(SD=0.158)*	0.062 *(SD=0.163)*	0.591 *(SD=0.141)*	0.042 *(SD=0.137)*	0.092 *(SD=0.184)*
	Engagement	1.601 *(SD=2.028)*	1.559 *(SD=1.846)*	1.734 *(SD=2.511)*	1.293 *(SD=1.358)*	2.100 *(SD=2.719)*
Macro	Likes	1.072 *(SD=1.724)*	0.945 *(SD=1.018)*	1.348 *(SD=2.661)*	0.913 *(SD=0.821)*	1.144 *(SD=1.999)*
	Comments	0.064 *(SD=0.430)*	0.083 *(SD=0.518)*	0.024 *(SD=0.044)*	0.126 *(SD=0.697)*	0.036 *(SD=0.218)*
	Engagement	1.136 *(SD=1.816)*	1.027 *(SD=1.205)*	1.371 *(SD=2.692)*	1.039 *(SD=1.169)*	1.180 *(SD=2.041)*

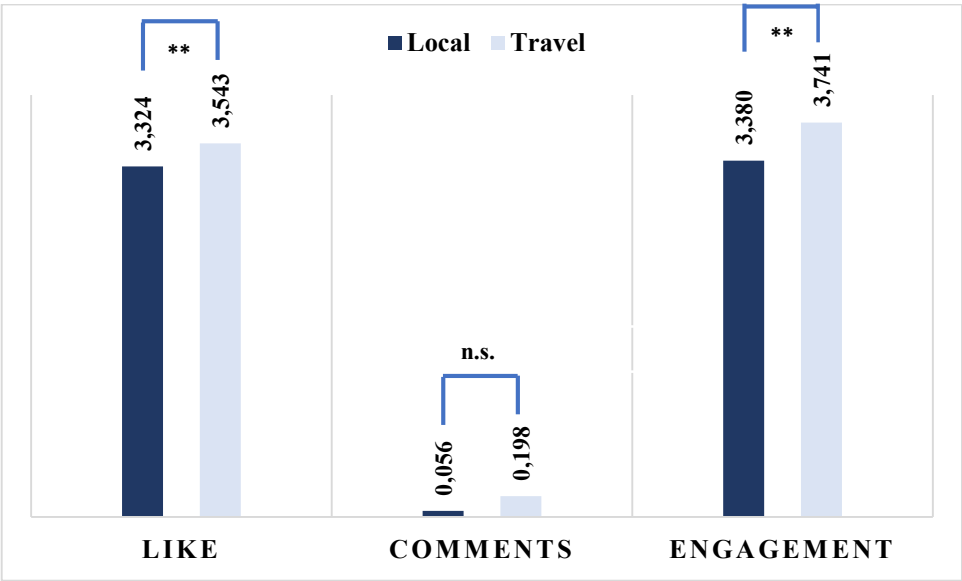
To achieve the objectives proposed in this research, a series of univariate generalized linear model (UGLM) analyses using IBM SPSS Statistics v.26 were conducted, with one analysis for each dependent variable: likes rate, comments rate, and engagement rate. This method facilitates the regression and analysis of variance for a dependent variable, using several factors or variables. Additionally, this methodology allows for the introduction of moderating effects (IBM, 2022), enabling the examination of whether the influencer's link to the destination (travel vs. local) and the sentiment of their posts (negative vs. positive) strengthened the influence of nano-, micro-, and macro-influencers on engagement.

The UGLM analysis reveals significant differences in the total likes, comments, and engagement rates across the influencer types (nano, micro, and macro), as detailed in **Table 4.** These results support **H1a**, **H1b** and **H1c**, confirming that influencer type significantly affects the likes ($F_{(2,\ 34{,}173)}$=475.99, p<0.01, η^2=0.027), comments ($F_{(2,\ 34{,}173)}$=35.25, p<0.01, η^2=0.002) and engagement rates ($F_{(2,\ 34{,}173)}$=467.71, p<0.01, η^2=0.027). Post-hoc analyses, using Tukey's HSD, confirm that nano-influencers have a significantly higher engagement rate than both micro- (Mean difference=3.125, p<0.01) and macro-influencers (Mean difference=3.590, p<0.01), with no significant difference between micro- and macro-influencers (Mean difference=0.465, p>0.1). Similarly, the likes rate is significantly higher for nano-influencers compared to micro- (Mean difference=2.972, p<0.01) and macro-influencers (Mean difference=3.440, p<0.01), and

marginally higher for micro- when compared to macro-influencers (Mean difference=0.468, $p<0.1$). The comments rate for nano-influencers is also significantly higher than for micro- (Mean difference=0.153, $p<0.01$) and macro-influencers (Mean difference=0.149, $p<0.01$), with no significant difference between micro- and macro-influencers (Mean difference=-0.003, $p>0.1$).

The UGLM analysis further indicates that influencer origin moderates the link between the influencer type and both likes ($F_{(2,\ 34{,}173)}= 4.65$, $p<0.01$, $\eta^2=0.000$) and engagement rates ($F_{(2,\ 34{,}173)}=4.20$, $p<0.05$, $\eta^2=0.000$), although the effect sizes are low. Contrary to expectations that the effect of influencer type would be stronger for local influencers due to their destination connection, the results do not support **H2a** and **H2c**. Additionally, there is no significant interaction effect between influencer origin and influencer type on the comments rate ($F_{(2,\ 34{,}173)}=0.13$, $p>0.1$, $\eta^2=0.000$), leading to the rejection of **H2b**. **Figure 5** graphically presents these interaction effects, illustrating that the difference in likes rate between nano- and macro-influencers is slightly higher for travel (3.543) than for local influencers (3.324). Similarly, the difference in engagement rate between nano- and macro-influencers is greater for travel (3.741) than for local influencers (3.380). The difference in the comments rate between nano- and macro-influencers remains low for both groups (0.056 for locals and 0.198 for travelers) and is not statistically significant.

Figure 5. Differences in likes, comments, and engagement rates between nano- and macro-influencers for local and travel influencers

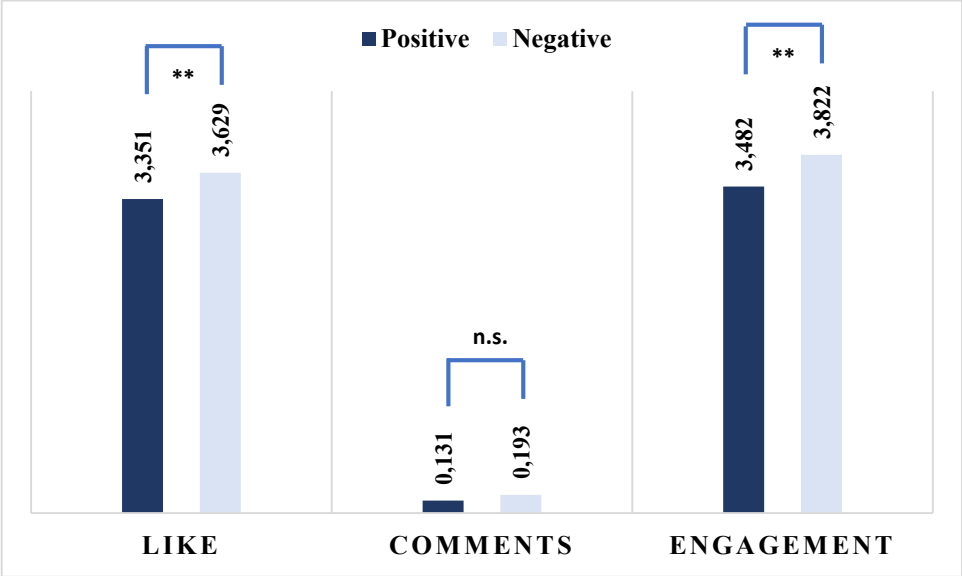


Note: ** significant difference; n.s. non-significant difference.

Finally, the UGLM analysis demonstrates that a negative sentiment in influencers' posts amplifies the effect of influencer type on both likes rate ($F_{(2,\ 34{,}173)}=9.22$, $p<0.01$, $\eta2=.001$) and engagement rate ($F_{(2,\ 34{,}173)}=8.66$, $p<0.01$, $\eta2=.001$), supporting **H3a** and **H3c**. No significant differences were observed for the comments rate, resulting in the rejection of **H3b** ($F_{(2,\ 34{,}173)}=0.21$, $p>0.1$, $\eta2=.000$). **Figure 6** illustrates that differences in likes and engagement rates between nano- and macro-influencers are greater for negative posts than for positive posts (3.629 vs 3.351 for likes, and 3.822 vs 3.482 for engagement). In

turn, differences in comments rate between nano- and macro-influencers are similar for both positive (0.131) and negative posts (0.193).

Figure 6. Differences in the like, comment, and engagement rates between nano- and macro-influencers in positive and negative posts



Note: ** significant difference; n.s. non-significant difference.

6. Discussion

This research investigated how influencer type (nano, micro, macro), destination connection (local versus travel), and post sentiment influence engagement with 34,175 Instagram posts from a cultural and gastronomic destination. The results yield important implications for theory and practice, particularly regarding the application of the strength of weak ties theory (Granovetter, 1973).

First, likes, comments, and engagement rates vary significantly by influencer category: nano-influencers consistently achieve the highest engagement, whereas macro-influencers exhibit the lowest rates. This outcome supports the strength of weak ties theory, indicating that closer influencer–follower relationships foster stronger engagement (Xu *et al.,* 2024). The most pronounced differences are observed between nano–micro and nano–macro influencers, while micro- and macro-influencers display more similar engagement patterns.

Second, contrary to initial expectations, travel influencers generate higher likes and engagement rates than local influencers across all categories. While local influencers are generally associated with authenticity and contextual relevance (Andrade-Cunha *et al.,* 2025), travel influencers may benefit from presenting novel, attraction-focused content that elicits stronger engagement responses (Ingrassia *et al.,* 2022). This approach often highlights visually prominent or iconic elements that align with audience expectations for inspirational travel content. Travel influencers may reach audiences less frequently exposed to destination-related content, thereby reducing content fatigue and increasing responsiveness. Collectively, these factors suggest that the higher engagement with travel

influencers may be attributed to differences in narrative framing and audience reception compared to local influencers.

Third, negative sentiment widens the engagement gap between nano- and macro-influencers more than positive sentiment does. Negative content generally results in higher engagement across influencer types, which is consistent with research indicating that there are stronger reactions to negative stimuli on social media (Boot *et al.,* 2021). The present findings extend this evidence by demonstrating that the effect is especially pronounced for nano-influencers.

Overall, engagement increases as emotional ties strengthen. These ties are to the influencer, the destination, or to the content. Variations in engagement are primarily driven by likes rather than comments, indicating that commenting behavior may be more influenced by content controversy or topic relevance than by influencer–follower emotional ties (Belanche *et al.,* 2025).

7. Conclusions and implications

7.1. Conclusions

This study demonstrates that the influence of influencers in the tourism industry cannot be accounted for solely by the reach criteria but must be accounted for through the lens of relational intensity and emotional bonds. By applying the strength of weak ties theory to a large-scale Instagram dataset, the findings indicate that nano-influencers always possess a higher engagement level due to their smaller number of followers, which generates a stronger emotional bond. Moreover, negative emotions have a magnifying effect on this process, suggesting that the intensity of affectivity enhances social influence in online environments. Finally, travel influencers outperform local influencers in terms of engagement, indicating that the inspirational and novelistic approach to message framing may be more efficacious than local authenticity in encouraging audience engagement.

7.2. Theoretical implications

This study extends Granovetter's (1973) strength of weak ties theory to tourism influencer marketing by demonstrating that follower count is a key determinant of engagement. Our results provide empirical evidence that nano-influencers, who maintain closer, more interactive relationships with their audiences, generate significantly higher engagement than micro- or macro-influencers. This reinforces recent applications of weak-tie theory in digital environments and clarifies how relational closeness shapes audience behavior toward tourism content (De Veirman *et al.*, 2017).

Second, by incorporating post sentiment as a moderating variable, this study advances the theoretical understanding of how emotional content interacts with tie strength towards the influencer (Aboalganam *et al.,* 2025). Negative sentiment amplifies engagement, particularly among nano-influencers, indicating that affective intensity strengthens the social influence process and serves as a boundary condition in digital engagement models (Xu *et al.,* 2024).

Finally, this research provides the first empirical comparison between local and travel influencers in a tourism context. The findings reveal that travel influencers generate

higher engagement, suggesting that content novelty can outweigh contextual authenticity in driving interaction. This underscores the importance of integrating novelty-seeking and destination familiarity into theoretical frameworks on influencer effectiveness (e.g., Casaló *et al.,* 2020).

This research has adopted a multi-method approach, combining the analysis of visual content (photos) using DL; the analysis of textual content (texts) using ML techniques; and the analysis of metadata such as comments, likes, and publication dates, which enables the filtering of the large dataset obtained. This approach enables the effective filtering of large datasets and can be applied to any local, regional, or national destination or hospitality service. It enhances understanding and broadens social science research by providing a comprehensive view of influencer engagement. This study also highlights the increasing accessibility of AI for big social media data analysis through open-source models (Zhang *et al.,* 2023).

Given the limited number of studies that analyze big datasets and integrate diverse data types, such as photographs, texts, and metadata (Filieri *et al.,* 2021), this combination of techniques helps addresses the underuse of multi-method research in travel and tourism.

7.3. Practical implications

This study provides actionable insights for DMOs aiming to optimize influencer selection and Instagram content strategy. First, it is indicated that influencer effectiveness should be evaluated not solely by follower count but by the strength of the influencer–audience relationship. Nano-influencers consistently achieve the highest engagement rates, demonstrating that smaller communities foster closer ties and more authentic interactions. As influencer fees increase sharply with audience size, DMOs may achieve greater impact at a lower cost by collaborating with multiple nano-influencers rather than relying on macro-profiles (Influencer Marketing Hub, 2025). For instance, industry estimates place the average cost of a single nano-influencer's post at approximately $55, compared to $5,250 for macro-influencers (Shopify, 2025). Reaching approximately 1.1 million users through nano-influencers would cost around $11,000, compared to an estimated $21,000 for macro-influencers, while generating significantly higher expected engagement (52,030 vs. 12,540 interactions). In other words, a large follower count may suggest a broad reach but does not guarantee meaningful engagement, highlighting the strategic value of collaborating with nano-influencers to promote destinations (Mariani *et al.,* 2021). Influencers with a sizable audience also appear to generate more authentic interactions (Rasel *et al.,* 2025).

Second, negative sentiment tends to drive higher engagement, particularly among nano-influencers whose audiences respond strongly to emotionally charged messages. While such content can increase visibility and virality, DMOs should exercise caution to avoid reputational risks. Instead of promoting negative narratives, DMOs are advised to actively monitor sentiment around the destination, especially among nano-influencers who wield significant persuasive power, establishing rapid response protocols to address emerging dissatisfaction and service failures (Abate *et al.,* 2026). This approach strengthens service recovery processes and reduces the likelihood that negative content will escalate into broader image crises.

Lastly, the influencer's origin also influences the engagement outcomes. Travel influencers achieve higher engagement across categories, likely due to the novelty and appeal of their content, making them effective at generating immediate reach and viral awareness. In contrast, local influencers contribute to sustained destination branding by reinforcing authenticity, cultural identity, and credibility, particularly in gastronomic and cultural contexts (Gomez *et al.,* 2018). DMOs can maximize their impact by combining travel influencers for short-term visibility with local influencers for long-term trust building and destination image reinforcement (Aboalganam *et al.,* 2025).

Beyond its managerial relevance, this study presents social implications related to the role of influencers in shaping tourist attitudes and behaviors. The greater engagement associated with nano-influencers indicates that influence increasingly operates within small, trust-based communities, where messages, both positive and negative, have a greater impact on perceptions, expectations, and decisions, thus increasing the social responsibility of influencer communication. The fact that certain profiles and emotionally charged content garners high levels of attention suggests that interest in destinations can be focused on specific places, narratives, or moments. Although this study does not directly measure tourist flows, this concentration of digital attention can contribute to uneven visitation patterns and increased tourist pressure, with social effects such as overcrowding, resident discontent, and the unequal use of public space. Finally, the differences between local and travel influencers demonstrate an unequal influence on destination representation. While travel influencers rapidly amplify visibility, local influencers tend to offer more stable perspectives based on everyday experiences. These dynamics create narrative imbalances in the visibility of local communities, with social implications about who defines and how the public image of the destination is constructed.

7.4. Limitations and opportunities for future research

Despite its meaningful contributions, this study presents several limitations that pave the way for future research. First, the analysis focuses on a cultural and gastronomic destination, which may limit the generalizability of the findings (Femenia-Serra & Gretzel, 2020). Although León attracts visitors with diverse motivations, its positioning differs from coastal, nature-based, or mass-tourism destinations. Future studies should replicate this methodological pipeline across different destination types to assess whether engagement patterns vary by tourism context.

Second, regarding our measures, the classification of influencers into travel and local categories relied on posting frequency and duration. While this approach follows established big-data tourism practices (Gunter & Önder, 2021; Gomez *et al.,* 2018), it may misclassify atypical cases, such as long-term visitors or residents with irregular posting habits. Future research should incorporate additional indicators, such as geolocation, contextual cues, and landscape–human interactions, given recent evidence showing that distinguishing locals from tourists in visual content significantly shapes interpretation and behavioral responses (Li et *al.,* 2025). Although our approach allows for the consistent, replicable classification of large-scale social media data, it may not fully capture an individual's connection to the destination (e.g. Belanche *et al*., 2017). Future research should complement behavioral metrics with measures of self-reported

connections to the destination, such as place identification or perceived authenticity, to develop a more theoretically grounded differentiation between local and travel influencers. Similarly, our multimodal sentiment variable was constructed by summing the text polarity and photo emotion scores, reflecting the assumption that textual and visual sentiment jointly contribute to the post's overall emotional valence. However, it could be useful for future research to confirm whether differential weighting across modalities is needed, depending on the relative importance of text or images for consumers when deriving the overall emotional valence of a post.

Third, although the dataset includes all publicly available Instagram photos posted between 2010 and 2022, the analysis excludes private accounts and other highly relevant formats such as videos, reels, and stories. Future studies should explore these content types to capture the dynamics of newer engagement mechanisms on Instagram.

Fourth, due to the characteristics of the analyzed destination, the dataset did not include mega-influencers. Further research is needed to examine how large-scale influencers operate in well-known destinations and whether their engagement dynamics differ from those of nano-, micro-, and macro-influencers.

Fifth, although AI models were applied to classify sentiment and emotions using validated ML and DL techniques, algorithmic bias remains possible, particularly when processing ambiguous facial expressions, multimodal irony, or sarcasm. Additional research could integrate hybrid approaches (human–AI annotation or topic modeling) and consider more nuanced influencer attributes such as specialization area, content style, and audience profile (De Veirman *et al.,* 2017).

Finally, to facilitate replication and expansion of this work, the analytical workflow developed in this study has been operationalized in the PhotoData Tour Analytics platform, enabling scalable multimodal data extraction and influencer profiling across diverse destinations. This tool can support future comparative studies and enhance the transferability of AI-based methodologies within tourism research.

References

Abate, Y. A., Ukpabi, D. C., & Karjaluoto, H. (2026), "Eco-influencers: a cross-generational investigation on the role of social media influencer marketing on green destination image", *Tourism Recreation Research,* Vol. 51 No. 1, pp. 94-114. https://doi.org/10.1080/02508281.2025.2450813

Agostino, D., Arnaboldi, M. and Calissano, A. (2019), "How to quantify social media influencers: An empirical application at the Teatro alla Scala", *Heliyon*, Vol. 5 No. 5, p. e01677. https://doi.org/10.1016/j.heliyon.2019.e01677

Aboalganam, K. M., AlFraihat, S. F., & Tarabieh, S. (2025), "The impact of user-generated content on tourist visit intentions: The mediating role of destination imagery", *Administrative Sciences,* Vol. 15 No. 4, pp. 117. https://doi.org/10.3390/admsci15040117

Andrade-Cunha, M., Irimia-Diéguez, A., & Perea-Khalifi, D. (2025), "Engagement and experience co-creation: An analysis of hotel Instagram profiles in Porto", *Journal of Tourism and Services,* Vol. 16, No. 30, pp. 143-164. https://doi.org/10.29036/3xhbty24

Bai, S., Li, Z., He, H. & Fan, W. (2025), "Engaging tourists from city aesthetics: evidence from multimodal analysis of computer vision and text mining", *Asia Pacific Journal of Marketing and Logistics.* https://doi.org/10.1108/APJML-02-2025-0287

Belanche, D., Casaló, L. V., & Flavián, C. (2017), "Understanding the cognitive, affective and evaluative components of social urban identity: Determinants, measurement, and practical consequences", *Journal of Environmental Psychology*, Vol. 50, pp. 138-153. https://doi.org/10.1016/j.jenvp.2017.02.004

Belanche, D., Casaló, L. V., Flavián, M., and Ibáñez-Sánchez, S. (2021), "Understanding influencer marketing: The role of congruence between influencers, products and consumers", *Journal of Business Research,* Vol. 132, pp. 186-195. https://doi.org/10.1016/j.jbusres.2021.03.067

Belanche, D., Ibáñez-Sánchez, S., Jordán, P. and Matas, S. (2025), "Customer reactions to generative AI vs. real images in high-involvement and hedonic services", *International Journal of Information Management,* Vol. 85, pp. 102954. https://doi.org/10.1016/j.ijinfomgt.2025.102954

Bhatt, P. and Pickering, C.M. (2023), "Analysing spatial and temporal patterns of tourism and tourists' satisfaction in Nepal using social media", *Journal of Outdoor Recreation and Tourism*, Vol. 44 No. Part A, p. 100647.

Blanco-Moreno, S., González-Fernández, A. M., Munoz-Gallego, P. A., and Casaló, L. V. (2024a), "Understanding engagement with Instagram posts about tourism destinations", *Journal of Destination Marketing & Management,* Vol. 34, pp. 100948. https://doi.org/10.1016/j.jdmm.2024.100948

Blanco-Moreno, S. (2024b), "*AI-powered insights: Analyzing visual and textual content on social media for destination marketing management"* (Doctoral dissertation, Universidad de León). DOI: 10.18002/10612/23009

Boot, A.B., Dijkstra, K. and Zwaan, R.A. (2021), "The processing and evaluation of news content on social media is influenced by peer-user commentary", *Humanities and Social Sciences Communications*, Vol. 8, pp. 209. https://doi.org/10.1057/s41599-021-00889-5

Borges-Tiago, M. T., Santiago, J., and Tiago, F. (2023), "Mega or macro social media influencers: Who endorses brands better?", *Journal of Business Research,* Vol. 157, pp. 113606. https://doi.org/10.1016/j.jbusres.2022.113606

Casaló, L. V., Flavián, C. and Ibáñez-Sánchez, S. (2020), "Influencers on Instagram: Antecedents

667 and consequences of opinion leadership", *Journal of Business Research*, Vol. 117, pp. 510–
668 519. https://doi.org/10.1016/j.jbusres.2018.07.005

669 Chrome. (2023), "Tab save - Chrome web store", available at:
670 https://chromewebstore.google.com/detail/tab-save/lkngoeaeclaebmpkgapchgjdbaekacki.

671 Chung, S., & Cho, H. (2017), "Fostering parasocial relationships with celebrities on social media:
672 Implications for celebrity endorsement", *Psychology & marketing,* Vol. 34 No. 4, pp. 481-
673 495. https://doi.org/10.1002/mar.21001Digital

674 Chung, J., Ding, Y. and Kalra, A. (2023), "I really know you: how influencers can increase
675 audience engagement by referencing their close social ties", *Journal of Consumer Research,*
676 Vol. 50 No. 4, pp. 683–703. https://doi.org/10.1093/jcr/ucad019

677 DataReportal. (2025), "Global overview report", available at:
678 https://datareportal.com/?utm_source=Statista&utm_medium=Data_Citation_Hyperlink&
679 utm_campaign=Data_Partners&utm_content=Statista_Data_Citation

680 De Veirman, M., Cauberghe, V., and Hudders, L. (2017), "Marketing through instagram
681 influencers: The impact of number of followers and product divergence on brand attitude",
682 *International Journal of Advertising*, Vol. 36 No. 5, pp. 798–828.
683 https://doi.org/10.1080/02650487.2017.1348035

684 Femenia-Serra, F. and Gretzel, U. (2020), "Influencer marketing for tourism destinations: Lessons
685 from a mature destination", in Neidhardt, J. and Wörndl, W. (Eds.), *Information and*
686 *Communication Technologies in Tourism 2020*, Springer, Cham, available at:
687 https://doi.org/10.1007/978-3-030-36737-4_6

688 Femenia-Serra, F., Gretzel, U. and Alzua-Sorzabal, A. (2022), "Instagram travel influencers in
689 #quarantine: Communicative practices and roles during COVID-19", *Tourism Management*,
690 Vol. 89, p. 104454. https://doi.org/10.1016/j.tourman.2021.104454

691 Filieri, R., Yen, D.A. and Yu, Q. (2021), "#ILoveLondon: An exploration of the declaration of
692 love towards a destination on Instagram", *Tourism Management*, Vol. 85, p. 104291.
693 https://doi.org/10.1016/j.jdmm.2024.100948

694 Ganguly, K.K. (2025), "Can Twitter data with positive or negative content affect individual
695 emotions related to travel & tourism decisions? A study pertaining to the COVID-19
696 pandemic", *Current Issues in Tourism,* Vol. 28, No. 2, 104992.
697 https://doi.org/10.1080/13683500.2023.2300044

698 Gomez, R., Gomez, L., Gibert, J. and Karatzas, D. (2018), "Learning from #barcelona instagram
699 data what locals and tourists post about its neighbourhoods", in Leal-Taixé, L. and Roth, S.
700 (Eds.), *Computer Vision – ECCV 2018 Workshops. ECCV 2018. Lecture Notes in Computer*
701 *Science*, Vol. 11134 LNCS, Springer, Cham, pp. 530–544.

702 Granovetter, M. (1973), "The strength of weak ties", *American Journal of Sociology*, Vol. 78 No.
703 6, pp. 1360–1380.

704 Gunter, U. and Önder, I. (2021), "An exploratory analysis of geotagged photos from Instagram
705 for residents of and visitors to Vienna", *Journal of Hospitality and Tourism Research*, Vol.
706 45 No. 2, pp. 373–398. https://doi.org/10.1177/1096348020963689

707 Han, J. and Chen, H. (2022), "Millennial social media users' intention to travel: the moderating
708 role of social media influencer following behaviour", *International Hospitality Review*, Vol.
709 36 No. 2, pp. 340-357. https://doi.org/10.1108/IHR-11-2020-0069

710 Hauer, T. (2022), "Importance and limitations of AI ethics in contemporary society", *Humanities*
711 *and Social Sciences Communications*, Vol. 9, pp. 272. https://doi.org/10.1057/s41599-022-
712 01300-7

Hauser, D., Leopold, A., Egger, R., Ganewita, H. and Herrgessell, L. (2022), "Aesthetic perception analysis of destination pictures using #beautifuldestinations on Instagram", *Journal of Destination Marketing and Management*, Vol. 24, p. 100702. https://doi.org/10.1016/j.jdmm.2022.100702

Himelboim, I. and Golan, G.J. (2023), "A social network approach to social media influencers on Instagram: The strength of being a nano-influencer in cause communities", *Journal of Public Relations Research*, Vol. 35 No. 1, pp. 20–37. https://doi.org/10.1080/15252019.2022.2139653

Horton, D., & Richard Wohl, R. (1956), "Mass communication and para-social interaction: Observations on intimacy at a distance", *Psychiatry.* Vol. 19 No. 3, pp. 215-229. DOI: 10.1080/00332747.1956.11023049

Influencer Marketing Hub, 2025. *Influencer Marketing Benchmark Report 2025*. Available at: https://influencermarketinghub.com/ebooks/influencer-marketing-benchmark-report-2025-hq.pdf [Accessed 15 May 2025].

Ingrassia, M., Bellia, C., Giurdanella, C., Columba, P. and Chironi, S. (2022), "Digital influencers, food and tourism—A new model of open innovation for businesses in the Ho.Re.Ca. sector", *Journal of Open Innovation: Technology, Market, and Complexity*, Vol. 8 No. 1, pp. 50. https://doi.org/10.3390/joitmc8010050

Instagram. (2023). *Instagram locations*. https://www.instagram.com/explore/locations/

Lee, M., Hong, J. H., Chung, S., & Back, K. J. (2021), "Exploring the roles of DMO's social media efforts and information richness on customer engagement: empirical analysis on Facebook event pages", *Journal of Travel Research,* Vol. 60 No. 3, pp. 670-686. https://doi.org/10.1177/0047287520934874

Lee, S. A., & Lee, M. (2017), "Effects of relationship types on customers' parasocial interactions: Promoting relationship marketing in social media", *Journal of Hospitality and Tourism Technology,* Vol. 8 No.1, pp. 133-147. https://doi.org/10.1108/JHTT-09-2016-0053

Li, Y. and Xie, Y. (2020), "Is a picture worth a thousand words? An empirical study of image content and social media engagement", *Journal of Marketing Research*, Vol. 57 No. 1, pp. 1–19. https://doi.org/10.1177/0022243719881113

Li, Y., Lee, H. H. M., & Blasco-Arcas, L. (2025), "Computer vision in branding: A conceptual framework and future research agenda", *Journal of Business Research,* Vol. 193, pp. 115329. https://doi.org/10.1016/j.jbusres.2025.115329

Lin, C.A. and Xu, X. (2017), "Effectiveness of online consumer reviews: The influence of valence, reviewer ethnicity, social distance and source trustworthiness", *Internet Research*, Vol. 27 No. 2, pp. 362–380. https://doi.org/10.1108/IntR-01-2016-0017

Mariani, M.M., Borghi, M. and Laker, B. (2023), "Do submission devices influence online review ratings differently across different types of platforms? A big data analysis", *Technological Forecasting and Social Change*, Vol. 189, p. 122296. https://doi.org/10.1016/j.techfore.2022.122296

Mariani, M.M., Ek Styven, M. and Nataraajan, R. (2021), "Social comparison orientation and frequency: A study on international travel bloggers", *Journal of Business Research*, Vol. 123, pp. 232–240. DOI: 10.1016/j.jbusres.2020.09.070

Microsoft Azure. (2025). *Computer Vision API - Azure Cognitive Services.* Retrieved from https://learn.microsoft.com/en-us/azure/cognitive-services/computer-vision/

Nigmatullina, K. and Rodossky, N. (2022), "Social media engagement anxiety: Triggers in news agenda", in Meiselwitz, G. (Ed.), *Social Computing and Social Media: Design, User*

Experience and Impact. HCII 2022. Lecture Notes in Computer Science, Springer, Cham, pp. 345–357.

NLTK. (2023), "SentimentAnalyzer", available at: https://www.nltk.org/api/nltk.sentiment.sentiment_analyzer.html.

Phantom Buster. (2023), "Phantom buster", available at: https://phantombuster.com/.

Rasel, M. A. B., Islam, M. R., Das, P. C., & Saini, S. (2025), "User influence, hashtag trends, and engagement patterns: analyzing social media network dynamics in tourism using graph analytics", *Tourism and Hospitality,* Vol. 6 No. 2, pp. 60. https://doi.org/10.3390/tourhosp6020060

Renton, M. and Simmonds, H. (2017), "Like is a verb: Exploring tie strength and casual brand use effects on brand attitudes and consumer online goal achievement", *Journal of Product and Brand Management*, Vol. 26 No. 4, pp. 365–374. https://doi.org/10.1108/JPBM-03-2016-1125

Salvador-Almela, M., Marine-Roig, E., & Arcos-Pumarola, J. (2025). "From pictures to perceptions: Instagram's role in shaping volunteer leisure experiences abroad"*, World Leisure Journal*, 1-25. https://doi.org/10.1080/16078055.2025.2480621

Serengil, S.I. (2023), "DeepFace", available at: https://github.com/serengil/deepface.

Shopify, 2025. *Influencer pricing: How much do influencers cost in 2025?*. Available at: https://www.shopify.com/blog/influencer-pricing [Accessed 17 May 2025].

Singgalen, Y.A. (2024), "Tourism and travel content analysis for market segmentation using toxicity and sentiment classification in Communalytic", *Building of Informatics, Technology and Science (BITS),* Vol. 6 No. 1, pp. 469-479 https://doi.org/10.47065/bits.v6i1.5294

So, K. K. F., Li, J., King, C., & Hollebeek, L. D. (2024), "Social media marketing activities, customer engagement, and customer stickiness: A longitudinal investigation", *Psychology & Marketing,* Vol. 41 No. 7, pp. 1597-1613. https://doi.org/10.1002/mar.21999

So, K. K. F., Li, X., & Kim, H. (2020), "A decade of customer engagement research in hospitality and tourism: A systematic review and research agenda", *Journal of Hospitality & Tourism Research,* Vol. 44 No. 2, pp.178-200. https://doi.org/10.1177/1096348019895562

Tafesse, W. and Wood, B.P. (2021), "Followers' engagement with instagram influencers: The role of influencers' content and engagement strategy", *Journal of Retailing and Consumer Services*, Vol. 58, p. 102303. https://doi.org/10.1016/j.jretconser.2020.102303

Venciute, D., Mackeviciene, I., Kuslys, M. and Correia, R.F. (2023), "The role of influencer–follower congruence in the relationship between influencer marketing and purchase behaviour", *Journal of Retailing and Consumer Services*, Vol. 75, p. 103506. https://doi.org/10.1016/j.jretconser.2023.103506

Wies, S., Bleier, A., & Edeling, A. (2023), "Finding goldilocks influencers: How follower count drives social media engagement", *Journal of Marketing,* Vol. 87 No. 3, pp. 383-405. https://doi.org/10.1177/00222429221125131

Xie-Carson, L., Magor, T., Benckendorff, P. and Hughes, K. (2023), "All hype or the real deal? Investigating user engagement with virtual influencers in tourism", *Tourism Management*, Vol. 99, p. 104779. https://doi.org/10.1016/j.tourman.2023.104779

Xu, X., Liu, J. and Liu, J.H. (2024), "The effect of social media environments on online emotional disclosure: tie strength, network size and self-reference", *Online Information Review*, Vol. 48 No. 2, pp. 390-408. https://doi.org/10.1108/OIR-04-2022-0245

Yoo, J.J., Kim, H. and Choi, S. (2024), "Expanding knowledge on emotional dynamics and viewer engagement: The role of travel influencers on YouTube", *Journal of Innovation & Knowledge*, Vol. 9 No. 4, 100616. https://doi.org/10.1016/j.jik.2024.100616

Yu, J., Dickinger, A., So, K.K.F. and Egger, R. (2024), "Artificial intelligence-generated virtual influencer: Examining the effects of emotional display on user engagement", *Journal of Retailing and Consumer Services*, Vol. 76, p. 103560. https://doi.org/10.1016/j.jretconser.2023.103560

Yu, J. and Egger, R. (2021), "Color and engagement in touristic Instagram pictures: A machine learning approach", *Annals of Tourism Research*, Vol. 89, p. 103204. https://doi.org/10.1016/j.annals.2021.103204

Yu, X., & Cheng, M. (2025), "Multimodality in tourism and hospitality: A critical and narrative review", *Tourism Management,* Vol. 111, pp. 105245. https://doi.org/10.1016/j.tourman.2025.105245

Zhang, K., Zhang, J. and Yang, J. (2023), "The influence of human elements in photographs on tourists' destination perceptions and intentions", *Tourism Management*, Vol. 95, p. 104684. https://doi.org/10.1016/j.tourman.2022.104684