
Social media management: Choose measures of success on Instagram

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Abstract

This study aims to demonstrate the different results of particular methods applied for answering the same research question. By conducting field study, Instagram marketing communication of higher education institutions is empirically investigated. This study provides insights into measures of user engagement on Instagram and to shed the lights on their differences by applying these metrics on real data. The results demonstrate that a) liking and commenting should be studied as separate constructs; b) the level of granularity chosen is important in evaluating Instagram marketing communication; c) control variables should not be neglected in evaluating Instagram marketing communication; d) likes(comments)-to-followers ratio is not appropriate variable to measure user engagement; e) including quasi-moderators to conceptual frameworks should be considered based on literature review. Thus, the contribution of this research is two-fold. On a theoretical level, it enhances the existing knowledge base on Instagram user engagement and construct operationalisation appropriate for studying user engagement. On a practical level, the findings from this study could guide evaluation of marketing and communication strategies for brands that employ Instagram as part of their digital marketing mix.

1. Introduction

The advent of the digital age has ushered in transformative shifts in how organizations communicate with their target audiences. Specifically, the proliferation of social media platforms has not only democratized information dissemination but also strategically redefined marketing paradigms. This has led to an increased usage of social media platforms as strategic marketing tools to engage consumers (Schultz, 2017). Among these platforms, Instagram stands out for its visually rich interface (Ting et al., 2015) and has thus emerged as a complex yet potent tool for marketers. According to Voorveld (2019), Instagram marketing represents a fertile ground for academic investigation, opening up avenues for research that could have profound implications for both theory and practice.

Consumer engagement is a fundamental construct for evaluating the effectiveness of social media marketing (see Schivinski et al., 2016; Lee et al., 2018; Aydin, 2020). As recent studies suggest (see Deng et al., 2023; Tafesse & Dayan, 2023; Tafesse & Wood, 2023), user engagement remains a focus of academic attention today. Despite the growing body of literature on user engagement with brand posts on social media (see Moro et al., 2016; Lee et al., 2018; Karpinska-Krakowiak & Modlinski, 2020), there are still substantial gaps in understanding the intricacies of engagement measurement and its influencing factors, specifically on Instagram. Deng et al. (2023) conducted a systematic review of literature, presenting an integrative framework that identifies key predictors of consumer engagement with brand posts on social media platforms. While their investigation offered noteworthy insights, it also unveiled a lack of Instagram-focused research, with only 12 out of 82 studies addressing this area. In addition, though current literature provides insights into operationalizing the construct of user engagement, there remains a void concerning the precise ways to study these variables and its predictors.

In response to this gap, this study aims to demonstrate the different results of particular methods applied for answering the same research question. By conducting field study, Instagram marketing communication of higher education institutions is empirically investigated. This study provides insights into measures of user engagement on Instagram and to shed the lights on their differences by applying these metrics on real data. Thus, the contribution of this research is two-fold. On a theoretical level, it enhances the existing knowledge base on Instagram user engagement and construct operationalisation appropriate for studying user engagement. On a practical level, the findings from this study could guide evaluation of marketing and communication strategies for brands that employ Instagram as part of their digital marketing mix.

2. Engagement

Engagement represents reactions of consumers or users on social media platforms. The terminologies utilized in the academic literature are varied; some refer to it as 'user engagement', while others call it 'social media engagement' or 'consumer engagement'. Despite the differences in terminology, the focus remains on the same underlying concept of gauging audience interaction with a post or social media account. The term user engagement will be used in the following text.

Numerous scholars, including De Vries et al. (2012), Peters et al. (2013), Schivinski et al. (2016), and Lee et al. (2018), universally concur that user engagement serves as an essential construct for evaluating the effectiveness of social media marketing. For Instagram, key measures of user engagement include views, likes, comments, and shares. These metrics can be accessed by an influencer or a brand through their profile, providing insight into the interaction between their content and the audience. However, among these metrics, only likes and comments are publicly accessible, posing limitations to external analysis. Given these considerations, conducting field studies (see Aydin, 2020; Devereux et al., 2020) provides an appropriate methodological approach for investigating user engagement, as it allows for in-depth, real-world exploration of the complex interplay between users, brands, and content within the social media landscape.

Case:

The higher education sector, acknowledged as dynamic and fiercely competitive (Chapleo & O'Sullivan, 2017), has found it imperative to adopt business-like practices and procedures (Gunina et al., 2019), with a focus on effective branding and marketing communication. As is the case with many organizations across industries, higher education institutions (HEIs) have leveraged social media as an indispensable marketing tool (Momen et al., 2019). However, merely establishing an online presence is insufficient (Bélanger et al., 2014; Carrillo-Durán & García, 2020). Universities are urged to create and publish content that is not only relevant but also appealing to their target audience (Sandvig, 2016).

Vividness, or media richness (see e.g. Shahbaznezhad et al., 2021), is related to perception and, according to Coyle and Thorson (2001) and De Vries et al. (2012), the degree to which a post or media message can stimulate different senses. According to Steuer (1992) and Fortin and Dholakia (2005), vividness reflects the breadth of the message, i.e., the amount of sensory stimuli (e.g., colour), and the depth of the message, i.e., quality and resolution. According to De Vries et al. (2012), a certain level of vividness can be achieved by

incorporating dynamic animations, colours or images into the message. According to the media richness theory introduced by Daft and Lengel (1986), the higher the level of media richness, the higher the effectiveness of the communication.

Colour, being a vital element of marketing communication (Gunina et al., 2017), significantly contributes to attracting consumer attention (Labrecque & Milne, 2012) and enhancing brand recognition (Bottomley & Doyle, 2006). Colour also plays a pivotal role in shaping consumer behaviour, evoking varied emotional responses and affecting their motivations (Aslam, 2006; Page et al., 2012). Understanding colour psychology can significantly differentiate a company from its competitors, enhance brand awareness, and more effectively target their specific audience (Singh, 2006; Labrecque & Milne, 2012). For instance, Yu et al. (2020) investigated colours in tourists' destination-related Instagram posts and found their impact on liking and commenting. In this context, social media managers must carefully select colour schemes to optimize consumer appeal and engagement. Thus, this empirical study seeks to answer the research question:

- *RQ1: How do colours used in Instagram content influence user engagement with brand posts?*

2.1. Likes and Comments

Instagram's likes and comments serve as primary metrics for quantifying user engagement. Since likes and comments reflect user interaction with a particular post, they thus are invaluable in evaluating content's effectiveness (Devereux et al., 2020; Bonilla-Quijada et al., 2020; Rietveld et al., 2020). However, it's critical to understand that these metrics embody distinct aspects of user engagement and thus should be analysed separately.

Firstly, sentiment differs significantly between these two metrics. Instagram likes typically express positive engagement: enjoyment, support, amusement, appreciation, recognition, or may confirm importance of the content (Lowe-Calverley & Grieve, 2018). On the contrary, as Markowitz-Elfassi et al. (2019) highlight, commenting does not necessarily denote positive attitudes. Comments can embody either positive or negative sentiments, and may instead be used to ridicule, ignite disputes, or contradict a post's content.

Secondly, the degree of user involvement varies between likes and comments. A 'like' on Instagram generally signifies a relatively low level of involvement, indicating a certain degree of interest or approval, but necessitating minimal effort or deliberation. However, comments represent a higher level of involvement, requiring users to articulate their thoughts, pay more attention and contribute intentionally to the discourse (Markowitz-Elfassi et al., 2019).

Thirdly, likes and comments may relate to different ways of stimuli processing. Dual-processing theory conceptualised in the Elaboration Likelihood Model (Petty & Cacioppo, 1986), which may be utilised in studies focused on user engagement (see Hughes et al., 2019; Dolan et al., 2019) explains this distinction. Rational content or posts that are particularly informative undergo detailed processing via the individual's central route, resulting in high involvement, e.g., commenting. Conversely, emotional content or visually appealing posts processed via the peripheral route result in a less conscious, more impulsive form of engagement, typically manifesting as likes. According to Kim and Yang (2017), liking represents affectively driven behaviour. Following this theory, particular post or content may earn more likes, but less comments, or vice versa.

Fourth, investigating the relationship between likes and comments enables a deeper, more comprehensive engagement analysis. For instance, De Vries et al. (2012) demonstrate that positive comments on brand posts correlate with the number of likes and comments, while negative comments do not positively relate to the number of likes. Thus, likes and comments should be treated as separate variables for a comprehensive understanding of Instagram engagement.

Case:

Based on this theoretical background, the following hypotheses are proposed:

- *H1a: Image colour influences Instagram post liking (number of likes).*
- *H2a: Image colour influences Instagram post commenting (number of comments).*

3. Granularity

An essential aspect of data analysis in social media research is granularity—the level of detail or depth of the analysis (Cohen et al., 2017). Selecting an appropriate granularity level enables precise measurement and meaningful analysis. For instance, absolute numbers of likes or comments are particularly indicative when the unit of study is a post, i.e., the granularity level is high. While investigating the influence of specific visual cues on engagement, posts with a studied cue are compared to posts lacking this cue. In this case, it is expected that a post containing the studied cue would gain more likes and/or comments. However, such a simple test of

differences would be reliable only if all posts were posted in the same time period by the same communicator (creator, influencer, or brand).

For example, a direct comparison of two posts (and the absolute numbers of likes they gain) — one with a particular visual cue from Influencer A and another without this cue from Influencer B — can be misleading. Any discrepancy may be attributed to varied audience sizes rather than the effect of the visual cue. Therefore, studies analysing data from multiple Instagram accounts often employ relative numbers, such as the ratio of likes (or comments) per post to the number of followers.

Case:

In this context, the following hypotheses were proposed:

- *H1b: Image colour influences Instagram post liking (likes to followers ratio).*
- *H2b: Image colour influences Instagram post commenting (comments to followers ratio).*

However, such an approach is not precise, as incorporating further metrics into the dependent variable decreases the testimonial ability of the analysis. The results of such analysis must be interpreted with caution. Thus, to take communicator characteristics (e.g., influencer's sex, sector, audience size) into account and to isolate their potential influence, some studies (see Tafesse & Wood, 2021) incorporate control variables into their research framework (for more details on control variables, see the next section).

Furthermore, time introduces an additional dimension of complexity in the analysis of social media engagement. As the number of likes and comments are cumulative metrics, older posts are likely to gather more of these engagements than newer ones. As a result, comparing an older post with a newer one, even if they originate from the same influencer, based solely on absolute numbers of likes or comments can lead to skewed results. The difference in engagement between these two posts may be attributed to the difference in the post's lifetime, as new likes and comments may accrue over time. Additionally, temporal considerations are also pertinent due to evolving Instagram algorithms (McWilliams, 2020; Mosseri, 2021; Mosseri, 2023). Posts from different timeframes—for instance, 2015 and 2021—cannot be validly compared on engagement metrics alone. The number of Instagram users is ever-growing, and the platform's modifications over time could impact the visibility and engagement of posts, even when the posts are from the same brand and its follower count remains consistent.

Although this underscores the potential influence of a post's age on user engagement, it is not always necessary to integrate this into the analysis as a control variable. As the numbers of likes and comments grow logarithmically over time, the inflow of these interactions tends to plateau once posts reach a certain age (e.g., a month after publication). Eger et al. (2021) ensured the stability of their engagement metrics by collecting data repeatedly with a time gap of two months (May and July 2019). They observed minimal divergence in datasets, affirming the diminishing effect of post age on engagement. This suggests that the time since publication may have limited implications for analyses conducted several months after the most recent post.

When analysing the influence of posting frequency on user engagement, different granularity levels may be applied. If the unit is a post, frequency may be measured by the time from the previous post and to the subsequent one, or, in other words, as a top position (see Schultz, 2017). Alternatively, a time period, such as a month or a week, may be the unit of analysis, with frequency measured as the number of posts per period. Here, the dependent variable becomes the average number of likes or comments per post within the specific time period.

When conducting research at the organisational level (e.g., brands within a specific industry), user engagement may be measured as the average number of likes (or comments) per post for a particular brand within a specified timeframe. Here, factors like sentiment or level of user involvement might hold less relevance, leading researchers to employ the engagement rate or engagement score as more suitable engagement metrics (see, e.g., Eger et al., 2021). As Deng et al. (2023) indicated, methods to calculate engagement scores vary; while some aggregate all types of engagement (e.g., Aydin, 2020), others attribute different weights to various types of user interactions (e.g., Karpinska-Krakowiak & Modlinski, 2020). Typically, these metrics are calculated in proportion to the number of followers (Eger et al., 2021), facilitating an unbiased comparison across various brands or influencers.

To demonstrate the potential difference between research at the organisational level of granularity and post level of granularity, the independent variable was adjusted from image colour to the colour scheme utilised by HEIs on Instagram. As mentioned earlier, Instagram post liking and commenting must be measured as the average number of likes and comments per post, respectively.

Case:

Therefore, the following hypotheses were proposed:

- *H1c: The colour scheme utilised by HEIs on Instagram influences Instagram post liking (average number of likes per post).*
- *H2c: The colour scheme utilised by HEIs on Instagram influences Instagram post commenting (average number of comments per post).*

A common modification to these engagement metrics involves logarithmisation, as used in some studies (see Tafesse & Dayan, 2023). This mathematical transformation aids in normalising skewed data, turning multiplicative or exponential relationships into additive ones, and equalising variance in datasets where variance increases with the mean. Notably, interpreting results from statistical models with a log-transformed dependent variable necessitates a translation back to the original scale, as coefficients represent the percentage change in the dependent variable per unit change in the independent variable.

4. Control variables

The bandwagon theory, introduced by Henshel and Johnston (1987) offers insight into the dynamic nature of user engagement. According to this theory, the number of followers serves as a form of social validation, stimulating further user engagement (Fu & Sim, 2011). The more followers a creator has, the more likely other users are to engage with their content. Users tend to evaluate and judge a profile based on the number of followers, aligning with the bandwagon effect (Metzger & Flanagin, 2013; De Vries, 2019). Lillqvist and Louhiala-Salminen (2014) further propose that a larger audience on social media platforms motivates users to engage more. Hence, it points out the direct influence of the number of followers on user engagement.

Delineating the factors that influence engagement, the role of the communicator—whether a creator, influencer, or brand—emerges as significant. If a study aims to primarily focus beyond the communicator's influence, these characteristics should be introduced as control variables. The definition of control variables, however, varies across disciplines. Some resources refer to control variables as constants—conditions unchanged throughout the research (*ceteris paribus*). In social media research employing field study, a control variable represents any variable that directly influences the dependent variables and at the same time is independent yet not the primary focus of the study (Babin & Zikmund, 2015) with no specific hypothesis concerning the relationship between control and dependent variables.

Control variables may be either categorical or numerical. For the purposes of regression analysis, the application of dummy variables offers a useful tool for representing categorical data in binary form (Allen, 2004). For example, when considering geographical region (e.g., CZ, SK, PL) as a categorical control variable, dummy variables can be employed. Thus, each country should be coded accordingly, where '1' meaning membership and '0' absence in a group, with one country serving as the default category.

Complementing this approach, covariates are the further important statistical tool. A common misconception, which appears in some studies, is considering covariates as any control variable. In fact, covariates are continuous control variables (Duignan, 2016). In the context of social media research, the absolute number of followers could serve as a covariate. However, using the absolute number of followers, communicators may be categorised into mega-influencers (over 1 million followers), macro-influencers (100,000 to 1,000,000 followers), micro-influencers (10,000 to 100,000 followers), and nano-influencers (fewer than 10,000 followers). These categories can further be transformed into dummy variables.

Case:

Here, the following hypotheses were proposed (see Figure 1):

- *H1d: Image colour influences Instagram post liking (number of likes).*
- *H2d: Image colour influences Instagram post commenting (number of comments).*

Although hypotheses H1d and H2d are similar to hypotheses H1a and H2a, they are intentionally named differently to compare results incorporated a control variable into conceptual framework.

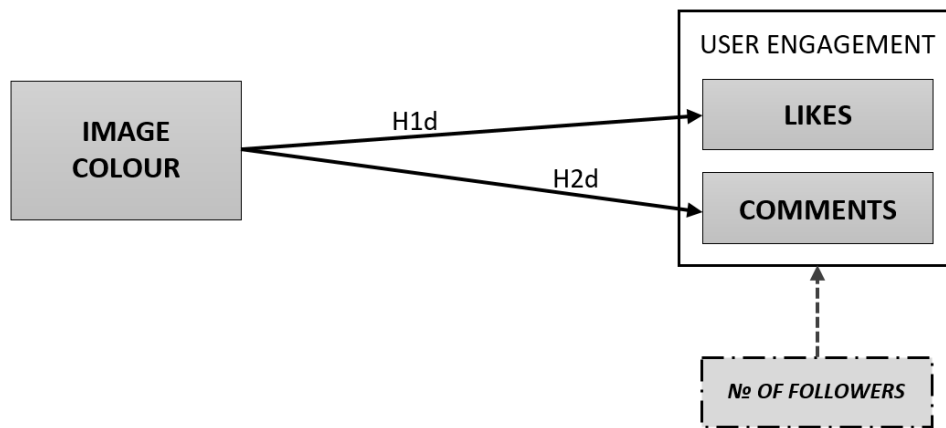


Figure 1. Conceptual framework D

Source: own processing based on literature review

4.1. Quasi-moderators

When investigating the intricate interplay between variables in social media management, moderators can offer valuable insights.

For instance, if a study were to explore how a visual cue, e.g., an emotional appeal, of Instagram content influences user engagement, the unit of analysis would be the Instagram post. As mentioned before, it's crucial to remember that comparing posts from multiple influencers, even within the same sector, using absolute values may not be appropriate. Imagine a scenario where posts of each influencer were analysed separately. Suppose the results show that emotional appeals influence user engagement, as measured by likes, but the strength of this influence varies among influencers. In this case, the communicator—whether a creator, influencer, or brand—may serve as a moderator. This suggests that variables describing the communicator (e.g., number of followers) impact the relationship between the independent variable (emotional appeal) and the dependent variable (user engagement).

As Eisend and Kuss (2019) suggest, moderators can explain the variation in effect size, illuminating conditions under which the relationship between variables strengthens or weakens. Thus, moderating effect of communicator characteristics may explain the fact that difference found in separate analysis. Though, researchers must also pay attention to their moderators' effect sizes and interpret it carefully, particularly when effect sizes are modest (Söderlund, 2023).

Furthermore, as Söderlund (2023) highlighted, incorporating moderators into a study should be well-grounded and supported by existing literature. In the context of user engagement research, proposing the moderating effect of the communicator is justified, given numerous previous studies exploring these effects (see Deng et al., 2023). The number of followers, which characterizes an Instagram account of a specific brand or influencer (creator), is an illustrative example of such a moderator (see Tafesse & Dayan, 2023).

Case:

Hence, the following hypotheses were proposed (see Figure 2):

- *H1e: Image colour influences Instagram post liking (number of likes).*
- *H2e: Image colour influences Instagram post commenting (number of comments).*
- *H3e: Number of followers moderates the influence of image colour on Instagram post liking (number of likes) and Instagram post commenting (number of comments).*

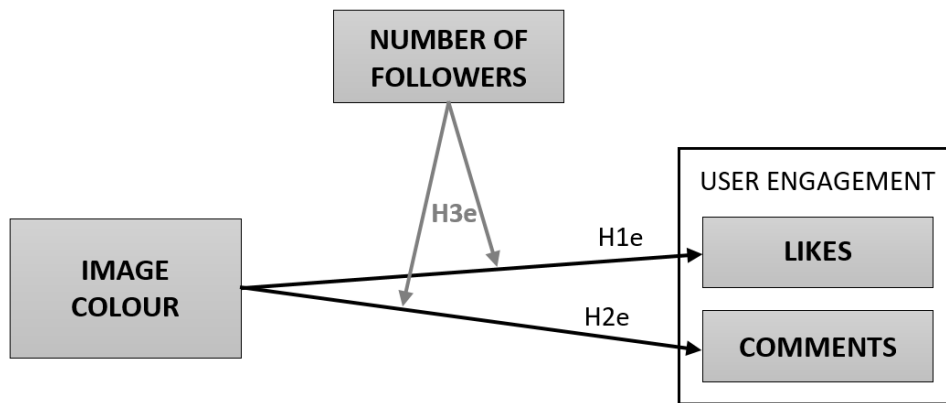


Figure 2. Conceptual framework E

Source: own processing based on literature review

Finally, it is noteworthy that some moderators, according to Söderlund (2023), may appear to be quasi-moderators. According to Sharma et al. (1981), quasi-moderators are variables influencing the relationship between independent and dependent variables (as a moderator), and at the same time correlates with either the independent (as a covariate) or dependent variable, or both. As mentioned before, the number of followers can directly affect user engagement, and may also moderate the relationship between stimuli and user engagement. Therefore, in the research, the number of followers could be treated as a quasi-moderator, providing a nuanced perspective on user engagement in Instagram marketing.

Case:

Ultimately, the following hypotheses were proposed (see Figure 3):

- *H1f: Image colour influences Instagram post liking (number of likes).*
- *H2f: Image colour influences Instagram post commenting (number of comments).*
- *H3f: Number of followers moderates the influence of image colour on Instagram post liking (number of likes) and Instagram post commenting (number of comments).*
- *H4: Number of followers influences Instagram post liking (number of likes) and Instagram post commenting (number of comments).*

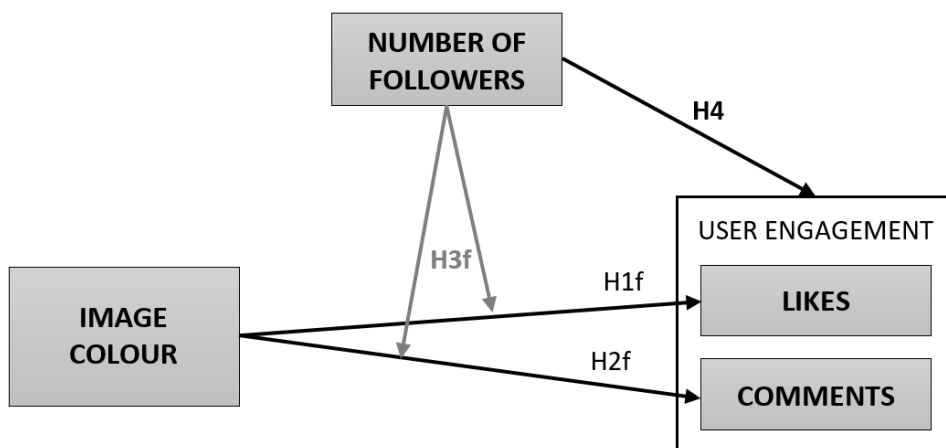


Figure 3. Conceptual framework F

Source: own processing based on literature review

5. Data and methods

This study adopted a thorough approach to collect data from the Instagram profiles of private HEIs in the Czech Republic. From a total of 27 private HEIs in the Czech Republic (Ministry of Education, 2023), the sample included data on 24 HEIs which had public Instagram profiles at the term of data collection. Data extraction of Instagram posts from private HEIs published in year 2022 was accomplished via a custom Python script and a tool known as Instaloader v4.9.6 (GitHub, 2023), a specialized tool designed for mining Instagram data, leading

to the successful collection of metadata and images from the selected HEIs on May 26, 2023. The resulting dataset contained 591 observations, with each observation corresponding to a single Instagram post. The repeat data collection was conducted in July 2023, approximately two months after the initial data collection. Reliability, or the degree of agreement between independent observations (May and July 2023), was analysed using Kendall's Tau correlation coefficient.

Google Cloud Vision API was utilized in the Python script to perform a detailed analysis of the dominant colours in the images. The resulting information, such as the image filename, RGB values, dominance score, and normalized RGB values of the dominant colour, was then added to the dataset. Each image was processed sequentially, with the Vision API examining their attributes. The dominant colour for each image was determined based on the colour score provided by the API, after which the corresponding RGB values and scores were extracted. To facilitate comparability, these values were normalized to a range between 0 and 1. During the data pre-processing stage, the RGB colour values were converted into the HCL colour model, where L is lightness, C-Chroma represents the purity or intensity of colour and H-Hue represents the value (from 0° to 360°, see Yu et al., 2020) on the colour wheel. The final variables in the dataset are presented in Table 1.

Table 1. Dataset variables

Variable	Variable Type	Data Type
Instagram post identification number	ID Categorical	Nominal
Instagram profile name	ID Categorical	Nominal
Number of likes on a post	Continuous, dependent	Numeric
Number of comments on a post	Continuous, dependent	Numeric
Hue	Continuous, predictor	Numeric
Chroma	Continuous, predictor	Numeric
Lightness	Continuous, predictor	Numeric
Number of followers on profile	Continuous, covariate/moderator	Numeric

Source: own processing

After removal of observations with missing data for one or more variables, the final sample included 310 observations.

In order to assess the impact of image colour characteristics on Instagram engagement metrics, multiple Linear Mixed-Effects Models (LMMs) and linear regression models were employed (Hayes, 2017). The colour attributes considered were lightness, chroma, and hue. All continuous variables were standardized to have a mean of 0 and a standard deviation of 1 for comparability. Two key dependent variables, namely the number of likes and the number of comments received on posts, were analysed. Additionally, several models incorporated follower count as a control or moderating variable to account for its potential influence. For LMMs, maximum likelihood estimation was used for model fitting, and 'username' was included as a random effect to control for individual differences across accounts. Significance levels were set at the conventional 0.05 threshold.

6. Findings

6.1. Impact of image colour on engagement

H1a. The results from the model revealed a significant influence of lightness on the number of likes an Instagram post received ($\beta = -1.0195$, $p = 0.0281$). This indicates that posts with higher lightness tended to receive fewer likes. The effects of chroma ($\beta = -0.6345$, $p = 0.1259$) and hue ($\beta = -0.1327$, $p = 0.3360$) on the number of likes were not statistically significant. Thus, among the examined colour attributes, only lightness had a significant impact on the number of likes an Instagram post received.

H2a. The model for the number of comments did not reveal any significant influence of the colour attributes. The p-values for lightness ($\beta = -0.001095$, $p = 0.799$), chroma ($\beta = -0.001851$, $p = 0.629$), and hue ($\beta = 0.000369$, $p = 0.766$) were all above the conventional 0.05 threshold for significance, suggesting that the colour of an Instagram post did not significantly affect the number of comments it received.

In summary, the findings indicate that while lightness significantly influenced the number of likes an Instagram post received, none of the examined colour attributes significantly influenced the number of comments.

6.2. Impact of image colour on engagement, using ratio

H1b. The model was fitted to the likes-to-followers ratio data, with lightness, chroma, and hue as predictors and username as a random effect. Lightness had a nearly significant effect on the likes-to-followers ratio ($\beta = -0.0012$, $p = 0.0747$), suggesting a trend for posts with higher lightness to have a lower likes-to-followers ratio, although this effect did not reach conventional levels of significance. Neither chroma ($\beta = -0.00073$, $p = 0.2271$) nor hue ($\beta = -0.00018$, $p = 0.3784$) had a significant effect on the likes-to-followers ratio.

H2b. The model for the comments-to-followers ratio indicated that only the intercept was significant ($\beta = 0.00027$, $p = 0.046$). None of the colour attributes significantly influenced the comments-to-followers ratio: lightness ($\beta = -0.00000011$, $p = 0.940$), chroma ($\beta = -0.0000011$, $p = 0.397$), and hue ($\beta = -0.000000019$, $p = 0.964$).

In summary, the results suggest that while there was a trend for lightness to negatively impact the likes-to-followers ratio, none of the colour attributes had a significant impact on the comments-to-followers ratio.

6.3. Impact of colour scheme of HEI on engagement

For H1c, the model (average likes as a function of average hue, lightness, and chroma) did not show any significant effects. The p-values for the estimated coefficients of average hue ($\beta = -4.733$, $p = 0.519$), lightness ($\beta = 3.025$, $p = 0.956$), and chroma ($\beta = 19.325$, $p = 0.682$) were all above the common significance threshold of 0.05, indicating that these variables did not have a statistically significant impact on the average number of likes per post.

For H2c, the model (average comments as a function of average hue, lightness, and chroma) yielded different results. While average hue did not significantly predict the average number of comments per post ($\beta = -0.0068$, $p = 0.1962$), both average lightness ($\beta = -0.1029$, $p = 0.0303$) and chroma ($\beta = -0.0919$, $p = 0.0263$) had significant effects. This suggests that the lightness and chroma of the colour scheme used by HEIs on Instagram do influence the average number of comments received per post. Specifically, for each unit increase in lightness and chroma, the average number of comments decreased by about 0.10 and 0.09, respectively.

In summary, these results indicate that while the colour scheme (measured in terms of hue, lightness, and chroma) used by HEIs on Instagram does not appear to significantly influence the average number of likes per post, it does have a significant impact on the average number of comments, with lightness and chroma showing significant negative associations.

6.4. Impact of image colour on engagement, with control variable

For H1d, lightness was significantly negatively associated with the number of likes ($\beta = -30.682$, $p = 0.0286$), indicating that posts with greater lightness tend to receive fewer likes, assuming all other variables remain constant. The other predictors, chroma, hue, and followers, did not significantly influence the number of likes at the 0.05 level.

For H2d, the standardized followers variable was the only significant predictor ($\beta = 0.43018$, $p = 0.01497$). This result suggests that accounts with more followers tend to receive more comments on their posts, assuming all other variables remain constant. The colour characteristics, lightness, chroma, and hue, did not significantly influence the number of comments at the 0.05 level.

In both models, significant variability in the intercept was observed across usernames, indicating that differences between users significantly influenced the number of likes and comments received. This is evidenced by the significant variance components for the username random effect in both models.

6.5. Impact of image colour on engagement, with moderator

H1e. The model revealed a significant effect of lightness on likes ($\beta = -30.658$, $p = 0.0288$), indicating that as lightness increases, the number of likes tends to decrease. The effects of chroma ($\beta = -20.581$, $p = 0.1282$) and hue ($\beta = -14.184$, $p = 0.3417$) on likes were not statistically significant.

H2e. None of the colour variables (lightness, chroma, and hue) significantly predicted the number of comments ($\beta = -0.03147$, $p = 0.8087$; $\beta = -0.05800$, $p = 0.6430$; $\beta = 0.04616$, $p = 0.7316$).

H3e. Regarding the number of likes, the model revealed a significant interaction between lightness and the number of followers ($\beta = 29.910$, $p = 0.0336$), suggesting that the influence of image lightness on likes varies depending on the number of followers. The interactions between followers and the other two colour variables (chroma and hue) were not statistically significant.

Concerning the number of comments, none of the interaction terms (lightness \times followers, chroma \times followers, hue \times followers) were statistically significant, suggesting that the number of followers does not moderate the relationship between image colour and the number of comments.

6.6. Impact of image colour on engagement, with quasi-moderator

For H1f, the results revealed a significant influence of lightness on the number of likes, as the standardized coefficient was negative ($\beta = -30.658$, $p = 0.0288$), suggesting that darker images were associated with higher liking. However, no significant relationship was found between chroma or hue and the number of likes (chroma: $\beta = -20.581$, $p = 0.1282$; hue: $\beta = -14.184$, $p = 0.3417$). Hence, H1f was partially supported.

For H2f, none of the colour attributes – lightness, chroma, or hue – had a significant impact on the number of comments (lightness: $\beta = -0.03147$, $p = 0.8087$; chroma: $\beta = -0.05800$, $p = 0.6430$; hue: $\beta = 0.04616$, $p = 0.7316$). Consequently, H2f was not supported.

For H3f, we found a significant interaction between lightness and follower count for post liking ($\beta = 29.910$, $p = 0.0336$). This implies that the effect of image lightness on likes was more pronounced for Instagram accounts with higher follower counts, thus partially supporting H3f. However, the interaction effects of chroma and hue with follower count were not significant, and no significant moderation effect of follower count was found for post commenting.

For H4 the data did not support a significant direct effect of follower count on the number of likes ($\beta = -34.696$, $p = 0.818$). However, there was a significant effect on the number of comments ($\beta = 0.4203$, $p = 0.016$), indicating that accounts with higher follower counts were associated with a higher number of comments.

6.7. Summary

Overall, for liking predictors, two hypotheses were supported (H1a and H1d), three hypotheses were partially supported (H1b, H1e and H1f) and one hypothesis was not supported (H1c, see Table 2). For commenting predictors, one hypothesis was supported (H2c) and five hypotheses were not supported (H2a, H2b, H2d, H2e and H2f). Moderating effect of the number of followers was partially confirmed (see H3e and H3f) and the direct influence of the number of followers on liking and commenting was partially confirmed (see H4).

Table 2. Summary of findings

Hypothesis	Outcome	Details
H1a	Supported	Lightness significantly influenced the number of likes, while chroma and hue did not.
H2a	Not Supported	None of the colour attributes significantly influenced the number of comments.
H1b	Partially Supported	Lightness had a nearly significant effect on the likes-to-followers ratio, but chroma and hue did not.
H2b	Not Supported	None of the colour attributes significantly influenced the comments-to-followers ratio.
H1c	Not Supported	The colour scheme used by HEIs on Instagram did not significantly influence the average number of likes per post.
H2c	Supported	The lightness and chroma of the colour scheme used by HEIs significantly influenced the average number of comments per post.
H1d	Supported	Lightness had a significant negative association with the number of likes, while chroma and hue did not.
H2d	Not Supported	None of the colour attributes significantly influenced the number of comments.
H1e	Partially Supported	Lightness significantly influenced the number of likes, while chroma and hue did not.
H2e	Not Supported	None of the colour attributes significantly influenced the number of comments.
H3e	Partially Supported	The number of followers moderated the influence of lightness on the number of likes, but not on the number of comments.
H1f	Partially Supported	Lightness significantly influenced the number of likes, while chroma and hue did not.
H2f	Not Supported	None of the colour attributes significantly influenced the number of comments.
H3f	Partially Supported	The interaction between lightness and follower count significantly influenced the number of likes, but not comments.
H4	Partially Supported	Follower count had a significant direct effect on the number of comments, but not on the number of likes.

Source: own processing

7. Discussion and conclusions

In the case of private HEIs, the influence of Instagram image colour on user engagement was studied. It was found, that lightness of Instagram post significantly influenced liking (H1a), but not commenting (H2a). It refers to the fact that **liking and commenting have different nature**, since likes and comments represent different levels of user involvement, where liking, as Markowitz-Elfassi et al. (2019) argue, requires less attention and commitment. Moreover, these findings are consistent with dual-processing theory and the Elaboration Likelihood Model of persuasion (see Petty & Cacioppo, 1986). Liking corresponds to affectively driven behaviour (Kim & Yang, 2017), less conscious and more impulsive type of engagement, so peripheral cues such as lightness have a greater influence on it. On the other hand, commenting requires a greater level of commitment, a greater level of involvement, more attention, and complex user responses (Markowitz-Elfassi et al., 2019), so commenting may depend more on the informativeness of the content than on colour.

Also, it is important to pay attention to **control variables**. In the model without the number of followers, lightness of Instagram post indicates a significant negative impact on post liking (for H1a, $\beta = -1.0195$, $p = 0.0281$). When using the number of followers as a control variable (or covariate), the negative impact of lightness on post liking is strong (for H1d, $\beta = -30.682$, $p = 0.0286$). It shows, that neglecting control variables may lead to the biased results, where the influence of predictor may be underestimated or overestimated.

Some studies, instead of using the number of followers as a control variable, deploy **likes(or comments)-to-followers ratio**. However, it does not bring the same results. In the model deploying the ratio of likes to the number of followers, lightness completely lost its significance (for H1b, $\beta = -0.0012$, $p = 0.0747$). It highlights the sad fact, that construct validity of liking operationalised and measured as likes(or comments)-to-followers ratio is low. Such indexes or ratios, according to its nature, give us information on what portion of followers (or employees/customers/acquisitions) liked (or commented) an Instagram post. But, as Lillqvist and Louhiala-Salminen (2014) mentioned, public Instagram profiles are visible for any user on Instagram, not only followers. Moreover, with dynamically changing Instagram algorithms (McWilliams, 2020; Mosseri, 2021; Mosseri, 2023), followers may simply not be exposed to the post at all, but non-followers would be. Thus, the simple fraction of number of likes (or comments) by the number of followers has nothing to do with message effectiveness. The size of fan base (or audience/organisation/customer base) is important in marketing communication research, as it may influence the engagement, and must be treated as a predictor, or a control variable, or a (quasi)moderator, but should not be included as a part of dependent variable.

Model operating with a number of followers as a **quasi-moderator** shows that lightness negatively influences Instagram post liking (for H1f, $\beta = -30.658$, $p = 0.0288$), and this influence is moderated by the number of followers (for H3f, $\beta = 29.910$, $p = 0.0336$). Firstly, it means that lightness has different effect on engagement on different levels of Instagram profile popularity. When the number of followers is low, the negative effect of high lightness on liking is more pronounced. With a high number of followers, the negative effect of lightness on liking is suppressed. Found moderating effect of the followers' number supports the integrative framework of Deng et al. (2023), which proposes the number of followers moderates the influence of different aspects of social media marketing on user engagement. Secondly, since the direct influence of the number of followers on liking was not significant (for H4, $p = 0.818$), the number of followers is a traditional moderator, but not quasi-moderator (as defined by Sharma et al., 1981). Thirdly, this could not be found if the model used likes(comments)-to-followers ratio as a dependent variable.

In a regression model with moderator, moderator is always incorporated in a formula as a part of interaction (predictorColour \times moderatorFollowers), but also as a control or dummy variable. Thus, the results of model with a moderator and a quasi-moderator are the same (see, e.g., H1e and H1f; H3e and H3f). The difference is in the focus and emphasis of a study. In the conceptual framework F (with a quasi-moderator), H4 is formulated for the influence of the number of followers on engagement, so this possible influence is studied and discussed. On the other side, the influence of the number of followers on engagement is out of the focus in the conceptual framework E. Moreover, the findings demonstrate, that **granularity** (see Cohen et al., 2017) of research is extremely important. It was found that lightness of an Instagram post significantly influenced liking of this post (H1a), but the effect of the average lightness value of Instagram post published by particular HEI on average number of likes per post (H1c) was not confirmed. Moreover, while the lightness and chroma of an Instagram post do not show significant influence on commenting (H2a), the results show, that the average lightness and chroma value of Instagram post published by particular HEI significantly influenced the average number of comments per post (H2c). Overall, the same construct of colour was studied and the same construct of user engagement, but within the different levels of granularity the opposite results were obtained. It cannot be judged, what way (and what results) are right, cause both levels of granularity may be applied, but they refer to the different purposes of measurement.

7.1. Theoretical contribution

By examining the constructs of liking and commenting separately, this research emphasizes that effects of Instagram post attributes (such as colour) on liking and commenting differ. These findings deepen our understanding of Instagram user engagement in terms of dual-processing theory and the Elaboration Likelihood Model (see Petty & Cacioppo, 1986). The findings of this research suggest that liking and commenting on Instagram posts should not be examined unitarily as a simple sum, nor as items of formula for calculating an index or ratio of user engagement.

Also, the findings of this study extend the state of knowledge in the sense that it highlights a salient bias occurs when likes(comments)-to-followers ratio is used for measuring user engagement and/or Instagram post effectiveness. By demonstrating the significant difference in the results of different approaches to user engagement operationalisation, this research contributes to the academic debate (see Dolan et al., 2019; Markowitz-Elfassi et al., 2019; Deng et al., 2023) on social media management and marketing communication effectiveness.

In this study, the effects of Instagram image colour on liking and commenting on were analysed at two levels of granularity. By putting emphasis on the discrepancy of the same constructs on engagement at different levels of granularity, this research highlights the importance of granularity in marketing and social media research. While evaluating the effects of Instagram marketing communication, an appropriate level of granularity should be chosen by researchers and practitioners with caution, because it may lead to the biased results.

7.2. Practical implications

The results of this research shed light on the fact that liking and commenting on Instagram posts depends on different aspects and to varying degrees. Although increasing Instagram user engagement may sound like a specific goal of Instagram marketing communications, it needs to be clarified whether the goal is to increase liking or commenting on Instagram posts. And depending on this, a different approach to communication strategies is needed, where, for liking increase, social media managers should work with the colour of Instagram post. However, if marketers or social media managers are aiming for a particular (e.g. future) Instagram post to reach a higher number of comments, then it is advisable to pay attention to factors other than image colour. In line with the Elaboration Likelihood Model (see Petty & Cacioppo, 1986), the rational or informative content of an Instagram post would play a more significant role here. Thus, for these two different purposes, the different post characteristics should have different weights in managerial decision-making.

Moreover, this study demonstrates that likes(comments)-to-followers ratio is not appropriate variable to measure user engagement and control variables should not be neglected in evaluating Instagram marketing communication. Using the ratio of number of likes(comments) to the number of followers may lead to the biased results, hide the possible moderating effects. Without using control variables, ostensible effects may be found, and these effects may be under- or overestimated.

From a practical perspective, it further highlights that the effects of Instagram post attributes on user engagement vary at different levels of granularity. This implies that when developing Instagram communication strategies and content plans, marketers and social media managers should be clear about whether the purpose is to increase engagement for a particular Instagram post, i.e. to increase the effectiveness of a marketing message or campaign, where the characteristics of individual posts need to be worked with. On the other side, is the purpose is to increase the average user engagement on the brand's Instagram profile, they should carefully set up a longer-term Instagram communication strategy for this purpose. Thus, the granularity level is essential not only for evaluating the effects of marketing communication, but also fort managerial decision-making and planning.

7.3. Limitations and future research

The main research limitations arise from the research design and the methods of data collection. As it was not possible in terms of research extent and technical feasibility to conduct a longitudinal study and obtain data on the values change (number of likes, comments, and followers) on specific Instagram profiles over time, values of all variables represent the status as of the date of data collection. For more accurate analyses, follow-up studies could obtain longitudinal data on user engagement and Instagram profile popularity, i.e., changing numbers of followers, likes, and comments a month, year or decade.

The construct of colour was operationalised (following the approach of Yu et al., 2020) as three variables: lightness, chroma and hue. However, hue was treated as a continuous variable with values from 0° to 360° in this case. Thus, future studies should focus on the differences in results obtained from the different ways of employing a variable in user engagement research and discuss the consequences of using continuous and categorical variables in analysis.

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