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Science communication in social Media: Analysis of success on TikTok, Instagram, and YouTube across scientific disciplines

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1. Science communication in the information society

In contemporary society—characterized by the centrality of digital technologies and the constant flow of information (Castells, 2006)—science communication has gained prominence as a vital bridge between scientific knowledge and the general public. This process goes beyond the mere transmission of information or media literacy; it serves as a key tool in fostering critically engaged, informed citizens who are prepared to confront global challenges (Castaño & Manresa, 2021; Buchanan, 2023).

Social media platforms enable direct communication between scientists and the public, prompting a reevaluation of the role of science in the public sphere and the communicative responsibilities of its representatives (Fernández-Muerza, 2019). However, the exponential increase in available information presents significant challenges: information overload and misinformation hinder the identification of reliable sources and the understanding of evidence-based knowledge (Moreno-Castro & López-Borrull, 2022).

The COVID-19 pandemic highlighted the crucial role of digital science influencers in combating misinformation through clear strategies and relatable examples, thereby enhancing public understanding (Valiati & Coelho, 2023). Thus, science communication is increasingly understood as a participatory and contextualized process, in which knowledge is collectively constructed, promoting a public culture, scientific culture that is critical, ethical, and grounded in evidence.

However, despite the growing recognition of science communication as a fundamental social tool, a significant gap remains: we still do not fully understand why some publications achieve remarkable success while others, with comparable scientific rigor, fail to gain visibility. Identifying the common elements shared by successful publications would allow science influencers to learn from them and replicate effective strategies. Currently, the lack of clear evidence on how to design science communication on social media that consistently reaches wide audiences represents a crucial challenge for both research and practice in this field.

1.1. Contextualized communication theory in social media-based science communication

Several theoretical frameworks help to understand the dynamics of science communication on social media. Goffman's *Theory of Self-Presentation* (1959) shows how scientists manage their public image through personal and humorous elements that build trust and emotional engagement, although this may sometimes replace critical evaluation and lead to uncritical acceptance of information. The *Theory of Human Communication* (Watzlawick et al., 1967) highlights that all behavior communicates, including silence and inactivity, shaping digital relationships. Similarly, the *Agenda-Setting Theory* (McCombs & Shaw, 1972) explains how algorithms and viral dynamics determine the visibility of scientific issues, while the *Uses and Gratifications Theory* (Katz et al., 1973) emphasizes the importance of understanding audience motivations—whether for information, entertainment, or social connection—to interpret participation and message reception.

Taken together, these theories explain how social media has profoundly transformed science communication, requiring new strategies adapted to today's digital culture.

1.2. Science communication on social media

Research shows that each digital platform attracts specific audiences and responds more effectively to particular communication formats—a phenomenon explained by *Audience Segmentation Theory* (Wind, 1978) and the *Uses and Gratifications Theory* (Katz et al., 1974). TikTok appeals to younger audiences through short-form visual content (Zhu et al., 2020); Instagram stands out for its use of visual formats such as images and infographics (Gao et al., 2020); while YouTube facilitates more in-depth scientific explanations (Allgaier, 2019).

This segmentation also occurs along disciplinary lines. Fields such as physics and mathematics benefit from long-form formats like those supported by YouTube; biology and medicine adapt well to brief, visually driven content on Instagram and TikTok; and the social sciences

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often utilize interactive formats to connect with audience (Kaplan & Haenlein, 2010; Maniou & Papa, 2023). Similarly, communicative effectiveness also depends on situational factors, as posited by the *Theory of the Communication Situation* (Bostrom & Heinen, 1977).

Assessing the impact of science communication requires specific indicators. In this line, metrics such as engagement rate, reach, interaction frequency, and view duration are essential for evaluating communicative effectiveness and optimizing strategy (Weiβ et al., 2024).

Ultimately, effective science communication on social media relies on a strategic understanding of digital environments, audience behavior, and content design. It necessitates the integration of communication theories and performance metrics to optimize message delivery and strengthen the science-society relationship in the digital age.

1.3. Aims and hypotheses

The general objective of this study is to analyze the key performance indicators (KPIs) of successful scientific content on TikTok, Instagram, and YouTube across various fields of knowledge.

The specific objectives are: (1) to examine the differential behavior across the selected social media platforms, and (2) to analyze variations in communication effectiveness across scientific disciplines.

2. Methodology

To address the complex dynamics of digital science communication, this study adopts a multi-method approach that integrates quantitative performance metrics (KPIs) with AI-based opinion and sentiment analysis. While previous research has typically relied on survey data or qualitative case studies to examine public engagement with science (Pelger and Nilsson, 2016), our methodology combines social network analysis (SNA) with emotional content analysis, thereby capturing both the structural and affective dimensions of online communication (see Fig. 1. Flowchart on methodology). This integration provides a comprehensive understanding of how visibility, interaction, and emotional tone converge to determine the success of scientific messages across different platforms. By jointly analyzing these dimensions, we offer a novel and easily replicable framework for studying the mechanisms through which scientific content gains traction in algorithm-driven environments, delivering both methodological innovation and practical insights for enhancing the reach and societal impact of science communication.

Previous studies have demonstrated the effectiveness of combining these techniques across diverse contexts. For example, research focusing on profiles from Instagram, Twitter, Facebook, and YouTube has employed SNA, sentiment analysis, and semantic coding to reveal platform-specific behavioral patterns. These include the case of child and youth influencers (Lozano-Blasco et al., 2023), gaming channels on YouTube (Lozano-Blasco et al., 2021), and official military profiles during crisis communication scenarios (Delgado Bujedo & Lozano Blasco, 2024; Quílez-Robles et al., 2023).

In this study, the sample selection is confined to a single period of time in order to observe network behavior. The cross-sectional approach allows for the comparison of characteristics across different social media profiles within one year and seven months, taken as the unit of analysis, without examining their evolution over time. The temporal limitation of the study precludes the establishment of causal relationships, while enabling comparisons among them, restricted to the dynamics of digital interaction (Taris et al., 2021).

2.1. Profile selection process and reliability

2.1.1. Profile search procedure

The search for social media profiles addressing scientific topics was structured using a combination of techniques.

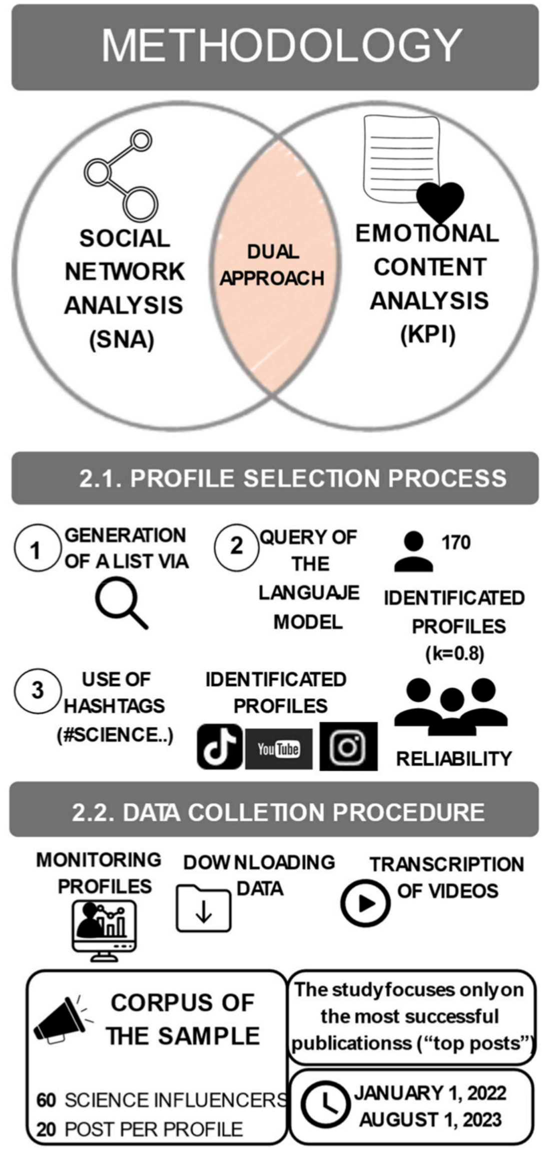


Fig. 1. Flowchart on methodology.

a. **First identification:** A list of candidate profiles was generated through HypeAuditor (https://goo.su/L1zuy0). HypeAuditor (2024) offers an all-in-one influencer marketing analytics platform, providing extensive tools for influencer discovery, audience quality assessment, fraud detection, and campaign management across major social media platforms. It was used by selecting the category "Top Science Influencers," from which the top 100 listed profiles were extracted.
b. **Secondly identification:** We queried the OpenAI language model ChatGPT (version GPT-4, March 2023) with the prompt: 'Which are the most relevant science influencers or content creators on YouTube, Instagram, and TikTok?' This approach yielded a more diverse set of candidate profiles, several of which overlapped with those identified through HypeAuditor
c. **Third identification:** Therefore, a third search strategy was implemented, based on the use of hashtags such as #science, #ciencia, #divulgación, # scientific dissemination, # popular science. Candidate profiles were subsequently ranked and selected according to their visibility on social media, specifically the number of likes and views obtained on Instagram, TikTok, and YouTube

Across the three strategies, a total of 170 (Instagram, TikTok and YouTube) unique profiles were identified. Those with the highest number of followers, interactions, and cross-platform presence were prioritized, as they consistently appeared across multiple search strategies.

2.1.2. Reliability procedure

To address this issue, an inter-rater analysis was conducted by a panel of three judges (Lombard et al., 2002) to evaluate the scientific quality of the selected profiles using the following. The three judges were graduate-level researchers in communication and science dissemination. All had training in qualitative content evaluation, and none had professional or personal links to the candidate profiles, which ensured impartiality. Prior to coding, the judges were provided with a coding manual and examples to calibrate their evaluation.

Judges applied a binary rating scale (1 = meets the criterion; 0 = does not), with an ordinal scale (0–2) used for borderline cases. A profile was included if at least two out of three judges agreed that it met the criteria. Inter-rater reliability was quantified using Fleiss' κ, yielding κ = .8, which corresponds to substantial agreement according to Landis and Koch's benchmark (Viera & Garrett, 2005). In cases of disagreement, final inclusion was resolved through consensus discussion.

To address concerns of representativeness and avoid sampling bias, the final selection comprised 60 profiles distributed across five disciplinary areas (Arts & Humanities, Health Sciences, Experimental Sciences, Social Sciences, and Engineering–Physics–Mathematics) were mapped to international classifications (UNESCO ISCED-F 2013; OECD, 2015) and balanced across three platforms (Instagram, TikTok, YouTube). This stratified sampling ensured that the study captured a diverse range of disciplines and platforms, enhancing both external validity and reproducibility.

The inclusion criteria are.

- Posts are meant to debunk myths, traditional knowledge, and pseudoscience.
- Content seeks to engage the audience with novel and intriguing information, such as enigmas, experiments, or top 10 lists.
- The complexity of science is demystified to make it more accessible, contributing to the democratization of expert knowledge.
- Language is approachable and incorporates the cultural jargon of the digital community.
- The content aims to approximate science to people, bridging the gap between scientific knowledge and popular understanding.
- The influencer explicitly seeks to disseminate scientific content.

2.2. Data collection procedure

2.2.1. Description of the platform for monitoring, capturing, and downloading data: FanPage karma

Once the science communication profiles were selected, they were monitored using the Fanpage Karma tool (https://www.fanpagekarma.com/es/inicio/). This social media analytics application enables the extraction of key performance indicators (KPIs) such as the number of likes, comments, followers, and other engagement metrics related both to individual posts and to the overall activity of any profile on social media platforms such as Instagram, TikTok, and YouTube. The KPIs analyzed (*comments, interaction, and likes*) are equivalent across the three platforms and were therefore calculated using the same standardized formula.

The platform also allows data to be collected over customized timeframes. In this study, profiles were examined from January 1, 2022, to August 1, 2023, covering a total period of 1 year and 7 months.

2.2.2. Extraction data

The extracted data were downloaded in Excel and CSV file formats, allowing for all posts to be sorted by number of likes. The 20 most successful posts were selected for further analysis.

2.2.3. Video transcription: speechnotes

Subsequently, each selected post—including its audio, video, and text content—was fully transcribed using Google's voice recognition tool (https://speechnotes.co/dictate/). This transcription enabled the application of sentiment analysis powered by artificial intelligence, allowing for an evaluation of the text's emotional tone (including polarity, agreement, subjectivity, and irony). The software used for sentiment analysis was MeaningCloud.

2.3. Sample corpus

The sample consists of 60 social media profiles from Instagram (20 profiles), YouTube (20 profiles), and TikTok (20 profiles), all belonging to science influencers. Within this selection, four profiles were chosen from each of the following areas of knowledge: Arts and Humanities, Social Sciences, Health Sciences, Experimental Sciences, and Engineering and Architecture.

From each profile, the 20 most-liked posts were selected, resulting in a total of 1200 videos. For each post, data were collected on key performance indicators (KPIs)—including number of likes, comments, reactions, post interaction rate, and overall engagement—as well as sentiment analysis for both the introductory message and the complete content. Sentiment variables included positive polarity, subjectivity, agreement, and irony. The timeframe for data collection spanned from January 1, 2022, to August 1, 2023.

It should be noted that the study relies exclusively on top posts; consequently, it delineates the upper bound of performance in highly successful publications that attain mass visibility, rather than the representative or average behavior of science communication profiles.

A detailed sociodemographic description of the sample is provided in Supplementary material 1, which includes each profile's self-description, the social media platform used, and their field of expertise, along with a brief overview of their content and communication style.

2.4. Data analysis

2.4.1. Statistical analysis with SPSS

The statistical analysis of KPIs and polarity (sentiment analysis) determined that although the sample distribution was approximately normal, heteroscedasticity was observed, as Levene's test was significant. Consequently, robust tests were applied: Welch's ANOVA whenever possible and, in cases where Welch was not applicable (e.g., Engagement by platform due to near-zero variance in one group), Kruskal–Wallis was used as a non-parametric alternative. For global analyses, means and standard deviations (SD) by group are reported, since the main contrasts were conducted on means (Welch ANOVA). In cases analyzed with Kruskal–Wallis, medians and interquartile ranges (IQR) are additionally presented as descriptive references. When global tests were significant, pairwise post-hoc comparisons were conducted using Welch's *t*-tests, with *p*-values adjusted via Holm's method to control for multiple comparison error. These results are complemented with effect sizes: η^2 and ω^2 for global effects, and Hedges' *g* with 95 % confidence intervals for pairwise comparisons (see Supplementary Material 2, Table S1–S4).

It should be noted that the sentiment analysis variables —agreement, subjectivity, and irony— are binary or ordinal categorical variables. Their distributions were compared across platforms (Table 2 and see Table S5 Supplementary Material 2) and across fields of knowledge (Table 4) using χ^2 tests of independence. In cases where more than 20 % of the cells had expected frequencies below 5, the Monte Carlo correction was applied or, for small tables, Fisher's exact test was used. Absolute frequencies and percentages, χ^2 values, raw and Holm-adjusted *p*-values, as well as effect sizes (Cramer's V) are reported (see

Supplementary Material 2, Table S2 and S4).

To examine associations between variables, correlation methods were selected according to each variable's level of measurement. Continuous variables (KPIs and polarity) were analyzed using Spearman's correlations (ρ), given that their distributions did not meet the assumptions of normality and homoscedasticity required by Pearson's coefficient. For polarity in relation to dichotomous sentiment variables (Agreement, Subjectivity, Irony), point-biserial correlations ($r$pb) were employed, which are equivalent to Pearson's correlation when one variable is dichotomous. Finally, associations between categorical variables were assessed using χ^2 tests of independence, with Cramer's V reported as the effect size. In this way, each association analysis is aligned with the measurement level of the variables involved, thereby avoiding biases arising from applying parametric correlations to categorical or ordinal data.

2.4.2. Sentiment analysis: meaning cloud

Sentiment analysis allows us to understand the emotions behind a text on social media by applying automated algorithms (Trisna & Jie, 2022). In other words, it is a social thermometer that measures the emotional reaction to a post or comment.

Sentiment analysis was performed using the MeaningCloud Sentiment Analysis API (v2.1), which implements a rule-based and semantic algorithm to classify text polarity and other affective features. The endpoint used was/sentiment-2.1, applied at the document level, meaning that each slogan or post caption was analyzed as a complete unit (PublicAPI, 2025).

Parameters were set to lang = es for Spanish texts and lang = en for English texts, and the general-purpose sentiment model (model = general) was applied (PublicAPI, 2025). Output was returned in JSON format and parsed for the following variables.

- Polarity: It analyzes whether the language used is emotional or lacking in emotion by categorizing texts according to the following values: very positive, positive, neutral, negative, very negative, or without emotion. A continuous score ranging from −1 (strongly negative) to +1 (strongly positive). In subsequent analyses, we used the numerical score directly.
- Subjectivity: It is a dichotomous variable that studies the connotative marks of the text, indicating whether the publication conveys an opinion (subjective) or describes a fact or circumstance (objective). Binary variable (classification: 0 = objective, 1 = subjective).
- Agreement: It indicates the concordance between the feelings detected in the text, sentence, or segment to which it refers. It is a categorical variable that indicates whether there is homogeneity or agreement of emotions or diversity (classification: 0 = disagreement, 1 = agreement).
- Irony: binary classification (0 = non-ironic, 1 = ironic). Provide a classification based on sarcasm or the absence of sarcastic intent.
- Confidence score: provided by MeaningCloud to indicate the reliability of the classification. Only outputs with confidence ≥60 % were retained; those below this threshold (<5 % of cases) were excluded.

This operationalization ensured that the sentiment variables were clearly defined and reproducible. Categorical variables (subjectivity, agreement, irony) were subsequently re-coded into binary format for statistical testing, while polarity was treated as a continuous–ordinal variable in line with its scale.

The official MeaningCloud repository on GitHub (Python plugin) specifies the sentiment analysis model in use and provides an SDK to facilitate its implementation (PublicAPI, 2025).

Ethical statement

All research data originated from publicly available content on social media platforms (Instagram, TikTok, YouTube). No private or personally identifiable information was accessed. All profiles analyzed are publicly available. Data collection complied fully with platform terms of service and applicable data protection laws.

The tools employed for data extraction and analysis—Fanpage Karma and HypeAuditor—adhere to current regulatory standards. Fanpage Karma's Privacy Policy explicitly references compliance with GDPR and Swiss FADP, implementing appropriate technical and organizational security measures, including IP masking, access control, and rights logging (Fanpage Karma, 2024). Similarly, HypeAuditor states that it complies with both GDPR and the California Consumer Privacy Act (CCPA) (HypeAuditor, 2025).

Artificial intelligence tools were also used: MeaningCloud API for sentiment analysis and ChatGPT (OpenAI GPT-4, March 2023) as a supplementary search aid. These tools were solely instruments for research and did not alter the underlying data.

Given that the study analyzes only publicly available information and does not involve direct interaction with human participants, ethical committee approval was not required under institutional guidelines.

3. Results

The analysis of key performance indicators (KPIs) revealed significant differences across platforms in the number of likes, comments, reactions, and interaction rate (see Table 1). After applying Holm's correction, engagement did not show significant differences between platforms, suggesting that this metric is not as discriminative once heteroscedasticity and multiple comparison adjustments are taken into account.

TikTok consistently outperformed Instagram and YouTube in likes, reactions, and comments, confirming its strong capacity to generate user interaction. In terms of interaction rate, TikTok also ranked first, followed by Instagram and, lastly, YouTube.

YouTube exhibited comparatively low performance in interaction per post, a striking finding given its status as a long-established digital content platform. However, its performance in overall engagement did not differ significantly once robust tests and multiple comparison adjustments were applied.

Although several of these differences were statistically significant, effect sizes ranged from small to moderate, indicating that while the differences are consistent, they do not reach large magnitudes (see Table 1 and Table S1).

Additionally, each uploaded post is accompanied by a description that typically includes hashtags, social challenges, or keywords. Significant differences were found in the polarity of these descriptions. Instagram shows a tendency toward positive polarity, whereas TikTok and YouTube lean more toward negative polarity. Although all three platforms gravitate toward neutrality overall, Instagram employs hashtags and social challenges with a more emotionally positive tone—possibly reflecting the utopian aesthetic often associated with the platform.

In the analysis of categorical variables derived from sentiment, slogans generally maintained a positive tone across all platforms, with no differences in the level of agreement. However, nuances emerged in subjectivity and irony. Slogans on Instagram and YouTube tended to carry a higher degree of subjectivity, whereas those on TikTok were characterized by a more objective style. Irony was generally infrequent, though it appeared more prominently on Instagram and, to a lesser extent, on YouTube.

By contrast, the content of the posts revealed much sharper distinctions. On Instagram and TikTok, a higher level of agreement was maintained, while on YouTube the absence of agreement clearly predominated. Moreover, YouTube content was distinguished by greater subjectivity and, notably, by a considerably higher use of irony, compared with the much lower presence of this resource on TikTok and Instagram (see Fig. 2).

Table 1
Comparison of publication performance indicators across platforms (Welch ANOVA/Kruskal–Wallis).

KPI	Platform	Mean	SD	Median	IQR	Levene's p	Overall test	Test statistic	raw p-value	η^2	ω^2	ε^2	Holm-corrected p
Likes	Instagram	77489.12	138479			0	Welch ANOVA	32.94	0	.08	.08		0
Likes	TikTok	468016	973496.6			0	Welch ANOVA	32.94	0	.08	.08		0
Likes	YouTube	101991.8	135890.1			0	Welch ANOVA	32.94	0	.08	.08		0
Comments	Instagram	827.27	1392.05			0	Welch ANOVA	39.47	0	.03	.02		0
Comments	TikTok	20760.06	87206.47			0	Welch ANOVA	39.47	0	.03	.02		0
Comments	YouTube	3564.60	6981.81			0	Welch ANOVA	39.47	0	.03	.02		0
Reactions	Instagram	78316.39	139486.7			0	Welch ANOVA	33.83	0	.08	.08		0
Reactions	TikTok	480632	996355			0	Welch ANOVA	33.83	0	.08	.08		0
Reactions	YouTube	105556.4	139439.1			0	Welch ANOVA	33.83	0	.08	.08		0
Post Interaction Rate	Instagram	.11	.22			0	Welch ANOVA	29.36	0	.01	.01		0
Post Interaction Rate	TikTok	.27	1.39			0	Welch ANOVA	2936	0	.01	.01		0
Post Interaction Rate	YouTube	.03	.07			0	Welch ANOVA	29.36	0	.01	.01		0
Engagement	Instagram	.11	.22	.06	.07	0	Kruskal-Wallis	471.15	0	.02	.02	.39	0
Engagement	TikTok	.32	1.40	0	.28	0	Kruskal-Wallis	471.15	0	.02	.024	.39	0
Engagement	YouTube	0	0	0	0	0	Kruskal-Wallis	471.15	0	.02	.02	.39	0

Table 2
Sentiment analysis of slogan texts and main Post content by social media Platform.

	Slogan Text Agreement	Slogan Text Subjectivity*	Slogan Text Irony*	Post Text Agreement*	Post Text Subjectivity*	Post Text Irony*	Slogan Polarity*	Post Polarity
Instagram	100.0%	33.0%*	2.0%*	46.2%*	58.2%*	2.3%*	+.54*	+.52
TikTok	100.0%	5.6%*	0.0%*	34.1%*	64.9%*	6.9%*	−.15*	+.23
YouTube	100.0%	24.6%*	0.3%*	10.7%*	79.5%*	24.0%*	−.29*	+.44

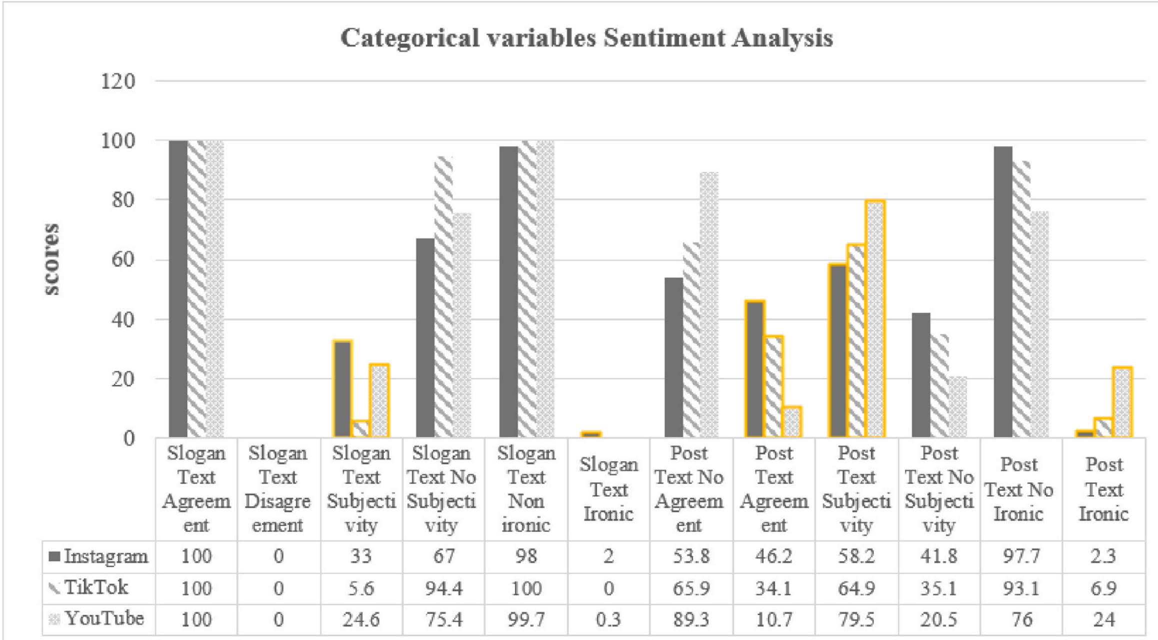
% / Polarity: 100, 50, 0

Note. Color intensity reflects the proportion (for categorical variables) or mean score (for polarity). Statistically significant differences between platforms ($p < .05$, Holm correction) are marked with an asterisk. Slogan text subjectivity differed across platforms (Instagram: 33.0 %, TikTok: 5.6 %, YouTube: 24.6 %). Differences were significant, $\chi^2 = 93.49$, $p < .001$, Cramer's V = .28 (Holm-corrected). The presence of irony in slogan text also varied (Instagram: 2.0 %, TikTok: .0 %, YouTube: .3 %), $\chi^2 = 12.54$, $p < .001$, Cramer's V = .10 (Holm-corrected). Post text agreement displayed a strong divergence across platforms (Instagram: 46.2 %, TikTok: 34.1 %, YouTube: 10.7 %), $\chi^2 = 119.87$, $p < .001$, Cramer's V = .32 (Holm-corrected). Post text subjectivity likewise differed significantly (Instagram: 58.2 %, TikTok: 64.9 %, YouTube: 79.5 %), $\chi^2 = 42.45$, $p < .001$, Cramer's V = .19 (Holm-corrected). Finally, post text irony varied substantially across platforms (Instagram: 2.3 %, TikTok: 6.9 %, YouTube: 24.0 %), $\chi^2 = 103.79$, $p < .001$, Cramer's V = .29 (Holm-corrected). The mean polarity scores: Slogan polarity was highest in Instagram (M = .54, SD = 1.75), followed by YouTube (M = −.29, SD = 2.15) and TikTok (M = −.15, SD = 1.37). The overall test was significant (Welch ANOVA, F = 24.93, $p < .001$, $\eta^2 = .04$). Post polarity did not differ significantly across platforms (Welch ANOVA, F = 2.40, p = .09, $\eta^2 \approx 0$). Source: Table S5 (supplementary material 2).

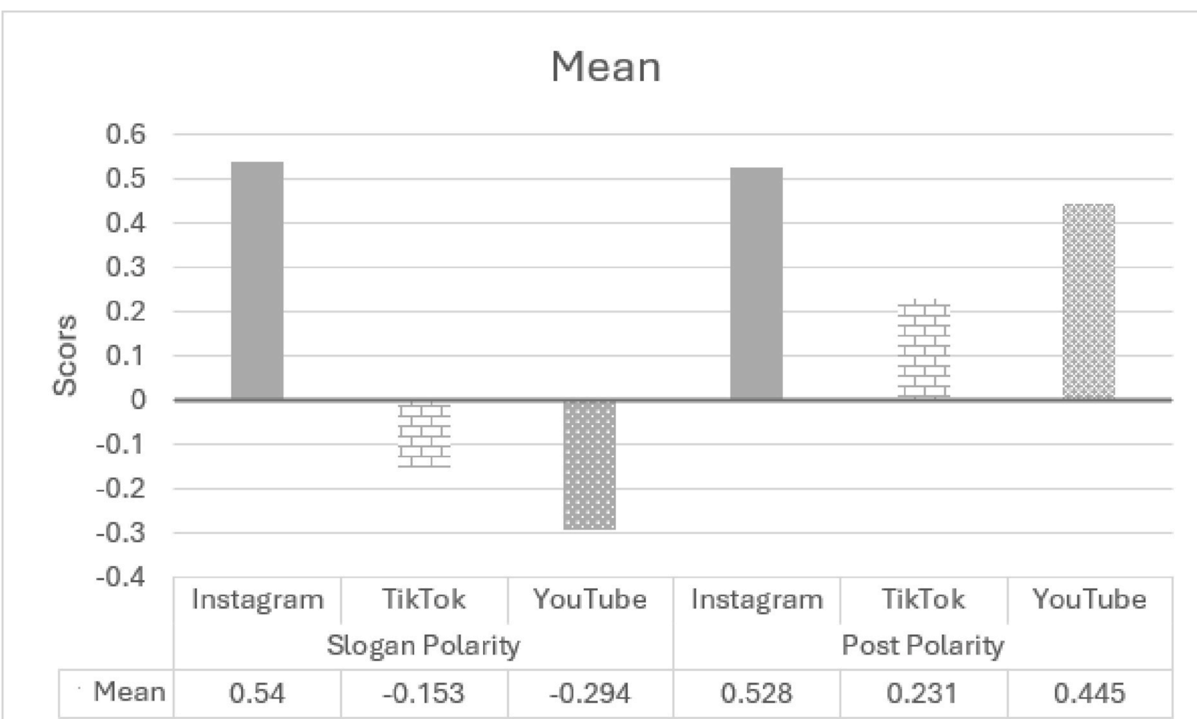
The analysis of polarity revealed significant differences across platforms. As Levene's test was significant, robust contrasts (Welch ANOVA/ Kruskal–Wallis) were applied. The overall results indicated small-to-moderate effects (η^2, ω^2, ε^2), suggesting that although statistically significant, the differences did not reach large magnitudes. Descriptive statistics showed that TikTok exhibited more extreme polarity values, YouTube tended toward neutrality, and Instagram occupied an intermediate position. Post-hoc comparisons using Welch tests with Holm correction confirmed significant differences, particularly between TikTok and the other two platforms. Effect sizes (Hedges' g with 95 % CI) are presented in Table S2 and S5 of Supplementary Material 2.

Welch's analysis of variance shows statistically significant differences in the polarity of slogans between platforms ($F(2, \ldots) = 24.93$, $p < .001$, $\eta^2 = .04$). In contrast, the polarity of posts did not reach significant levels ($F = 2.41$, $p = .091$).

Differences in the performance of key performance indicators (KPIs)



Note: *Data that is statistically significant is highlighted in yellow. Slogan Text Subjectivity Total χ^2=93.50, p=0.000, V=0.28; Slogan Text Ironic Total: χ^2=12.55, p=0.004, V=0.10; Post Text Agreement Total: χ^2=119.87, p=0.000, V=0.32; Post Text Subjectivity Total: χ^2=42.45, p=0.000, V=0.19; Post Text Ironic Total: χ^2=103.79, p=0.000, V=0.30*



Note. *Slogan Polarity: Welch ANOVA, F = 24.93, p < .001, η² = .04*

Fig. 2. Sentiment analysis by platform (Instagram, TikTok, YouTube).

were observed across fields of knowledge (see Table 3). Robust global tests (Welch/Kruskal) revealed statistically significant variations in all indicators, with effect sizes ranging from small to moderate ($\eta^2/\omega^2 \approx$ .01–.06).

Profiles associated with Engineering consistently stood out by reaching the highest values in likes, reactions, interaction rate, and engagement. By contrast, profiles in the Social Sciences obtained the largest number of comments, whereas Engineering profiles generated comparatively fewer comments from their audience.

Post-hoc analyses confirmed that the lowest-performing area (Arts and Humanities) differed significantly from most of the others, particularly in likes, reactions, and comments (see Supplementary Material 2, Table S3, for pairwise comparisons, Holm-adjusted p-values, and Hedges' g effect sizes with 95 % CI).

Regarding the descriptions accompanying the posts, significant differences were found across fields of knowledge in terms of sentiment analysis. In the slogans, the level of Agreement was uniform across all disciplines, reaching 100 % in each area, with no statistically relevant differences. However, significant differences did emerge in Subjectivity: while most slogans in Arts and Humanities and in Health Sciences remained objective, a much greater use of subjective expressions was observed in Experimental Sciences and Engineering–Physics–Mathematics. Irony in slogans was generally very infrequent, though it appeared marginally in Arts and Humanities as well as in Health and Experimental Sciences, and was completely absent in Social Sciences and Engineering (see Table 4).

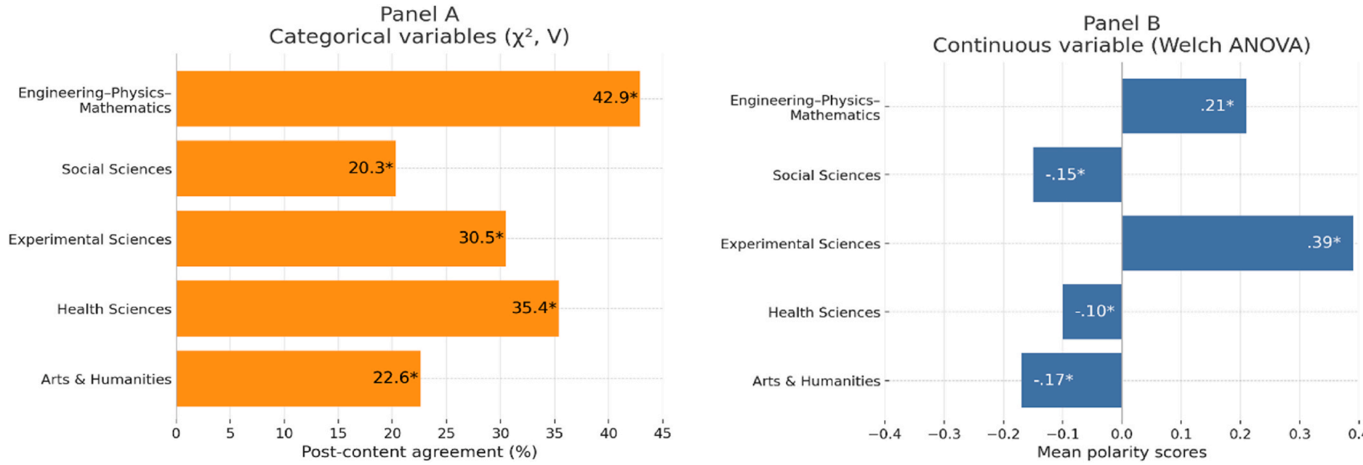
In the post content, the differences were even more pronounced. Agreement was higher in areas such as Engineering and Health Sciences, whereas a lack of agreement predominated in Arts and Humanities and Social Sciences. Regarding Subjectivity, the highest proportions were observed in Experimental Sciences, followed by Arts and Humanities, while Health and Social Sciences showed much lower values. Finally, the use of irony was particularly prominent in Experimental Sciences and Social Sciences, in contrast with Health Sciences (see Table 4).

Taken together, these findings indicate that while slogans maintain a largely positive and minimally ironic tone, more marked disciplinary differences emerge in post content. Experimental Sciences and Engineering stand out for their greater tendency toward subjectivity and

Table 3
Key performance indicators (KPIs) across fields of knowledge: descriptive statistics, overall tests, and effect sizes.

KPI	Area	Mean	SD	Levene's p	Overall test	Test statistic	raw p-value	η^2	ω^2	ε^2	Holm corrected p
Likes	Arts and Humanities	50835.94	46282.25	0	Welch ANOVA	27.55	0	.04	.04		0
Likes	Health Sciences	194379.4	388404.6	0	Welch ANOVA	27.55	0	.04	.04		0
Likes	Experimental Sciences	300946,3	775962.8	0	Welch ANOVA	27.55	0	.04	.04		0
Likes	Social Sciences	117949,9	212286.6	0	Welch ANOVA	27.554	0	.04	.04		0
Likes	Engineering	413358,4	958106.5	0	Welch ANOVA	27.554	0	.04	.04		0
Comments	Arts and Humanities	1018.64	1657.69	0	Welch ANOVA	14.90	0	.05	.05		0
Comments	Health Sciences	1726.90	2954.9	0	Welch ANOVA	14.90	0	.058	.05		0
Comments	Experimental Sciences	2299.89	4946.81	0	Welch ANOVA	14.90	0	.05	.05		0
Comments	Social Sciences	32869.58	110727.9	0	Welch ANOVA	14.90	0	.05	.05		0
Comments	Engineering	3871.61	9153.22	0	Welch ANOVA	14.90	0	.05	.05		0
Reactions	Arts and Humanities	51975.43	47090.8	0	Welch ANOVA	27.731	0	.04	.04		0
Reactions	Health Sciences	202218	408929.9	0	Welch ANOVA	27.73	0	.04	.04		0
Reactions	Experimental Sciences	306341.3	787983.3	0	Welch ANOVA	27.73	0	.04	.04		0
Reactions	Social Sciences	123919.3	221854.2	0	Welch ANOVA	27.73	0	.04	.04		0
Reactions	Engineering	421316.4	981106.8	0	Welch ANOVA	27.73	0	.04	.04		0
Post Interaction Rate	Arts and Humanities	.05	.11	0	Welch ANOVA	14.05	0	.01	.01		0
Post Interaction Rate	Health Sciences	.19	.39	0	Welch ANOVA	14.05	0	.018	.01		0
Post Interaction Rate	Experimental Sciences	.08	.22	0	Welch ANOVA	14.05	0	.01	.01		0
Post Interaction Rate	Social Sciences	.03	.05	0	Welch ANOVA	14.05	0	.018	.01		0
Post Interaction Rate	Engineering	.33	1.76	0	Welch ANOVA	14.05	0	.01	.01		0
Engagement	Arts and Humanities	.05	.11	0	Welch ANOVA	7.09	0	.01	.01		0
Engagement	Health Sciences	.17	.39	0	Welch ANOVA	7.09	0	.01	.01		0
Engagement	Experimental Sciences	.07	.22	0	Welch ANOVA	7.09	0	.01	.01		0
Engagement	Social Sciences	.10	.27	0,004	Welch ANOVA	7.09	0	.01	.01		0
Engagement	Engineering	.31	1.76	0	Welch ANOVA	7.09	0	.01	.01		0

Table 4
Sentiment analysis of slogan texts and main content across knowledge Areas.



Area	Post-content agreement (%)	Panel B (polarity)
Arts & Humanities*	22.6	−.17
Health Sciences*	35.4	−.1
Experimental Sciences*	30.5	.39
Social Sciences*	20.3	−.15
Engineering–Physics–Mathematics*	42.9	.21

Area	Mean polarity scores
Arts & Humanities*	−.17
Health Sciences*	−.1
Experimental Sciences*	.39
Social Sciences*	−.15
Engineering–Physics–Mathematics*	.21

Note. Panel A displays post-content agreement (%) across knowledge areas: Arts & Humanities (22.6), Health Sciences (35.4), Experimental Sciences (30.5), Social Sciences (20.3), and Engineering–Physics–Mathematics (42.9). Differences among areas were significant, $\chi^2(4) = 38.87$, $p < .001$, Cramer's V = .18 (Holm-corrected); therefore. Panel B displays mean polarity scores across the same areas: Arts & Humanities = −.17, Health Sciences = −.10, Experimental Sciences = .39, Social Sciences = −.15, and Engineering–Physics–Mathematics = .21. The overall test was significant (Welch ANOVA, $F = 4.32$, $p < .001$, $\eta^2 = .01$). Source: Table S6 (supplementary material 2).

agreement, whereas Social Sciences show a comparatively high frequency of irony, in contrast with Health Sciences, which are characterized by a more objective and less ironic style (see Table 4, and see Table S6 Supplementary Material 2).

Significant differences in Polarity were also found across fields of knowledge (Table 4). In this case, global effect sizes were of moderate magnitude (η^2, ω^2, ε^2), indicating a clearer influence of disciplinary domain on message tone. Profiles in Engineering and Experimental Sciences tended to display more extreme polarity values, while Arts and Humanities were characterized by lower values closer to neutrality. Post-hoc comparisons confirmed these differences, particularly between Arts and Humanities and the scientific–technical fields. Details of these comparisons, together with effect sizes (Hedges' g with 95 % CI), are reported in Table S4 of Supplementary Material 2.

The analysis of KPIs requires brief data processing to evaluate the interaction rate of each post. In this context, reach is calculated as likes/reach (i.e., number of reactions divided by number of followers), which serves as a metric for assessing the quality of engagement with the influencer's audience. In other words, it reflects whether the audience resonates with the content and is willing to interact.

This highlights the need for a correlation analysis (see Table 5). The correlation analysis revealed consistent associations between performance indicators (KPIs) and message polarity. Overall, correlations ranged from low to moderate in magnitude, suggesting that the emotional tone of posts is somewhat related to their capacity to generate interaction, but does not represent the primary determinant of performance.

Spearman correlations indicated that polarity values were significantly associated with certain interaction-related KPIs, particularly the number of likes and total reactions, where more positive polarity tended to correspond with a higher volume of positive audience responses. However, the magnitude of these associations was small ($\rho < .30$), pointing to a limited effect.

Regarding point-biserial correlations, significant associations were detected between polarity and specific binary sentiment categories. In particular, subjective messages and those containing irony tended to correlate with more extreme polarity values (either positive or negative), whereas more objective content was associated with polarity values closer to neutrality. These associations were likewise of low to moderate magnitude.

Taken together, the correlation (see Table 5a and 5b) results reinforce the findings from the comparative analyses: polarity and sentiment-related features of messages are linked to interaction indicators, but their contribution is limited compared to other factors inherent to platform and disciplinary domain.

The results of the Spearman correlation (see tabla 5.a) and point biserial correlation (see Table 5b) analyses reveal robust associations among social media engagement metrics. Notably, there is a strong positive relationship between the number of likes, comments, and shared reactions, indicating that different forms of interaction tend to co-occur: as one increases, the others generally increase as well. This convergence supports the notion that social media engagement reflects an integrated behavioral pattern, in which different modes of response are not independent but instead represent a unified process of audience involvement.

Table 5
Correlations analysis.

5.a Spearman correlation by ordinal variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1.Fans		.73***	.79***	.72***	.07*	−.13***	−.07*	.09**	−.31***	−.10**	−.12***	−.19***	.05	−.12***
2. Number of likes	.73***		.74***	1.00***	.26***	−.14***	.10***	−.16***	−.04	.05	−.02	.48***	.02	−.18***
3. Number of comments	.79***	.74***		.72***	.07*	−.17***	−.03	.22***	−.24***	−.04	−.25***	.09**	−.07*	−.13***
4. Number of reactions, comments, and shares	.72***	1.00***	.72***		.26***	−.15***	.08**	−.22***	−.06*	.04	−.02	.48***	.02	−.18***
5. Post interaction rate	.07*	.26***	.07*	.26***		.32***	.77***	−.15***	.20***	0	.17***	.29***	.01	−.04
6. Comments per post	−.13***	−.14***	−.17***	−.15***	.32***		.51***	.08**	.50***	−.13***	.35***	−.02	.14***	.02
7. Engagement	−.07*	.10***	−.03	.08**	.77***	.51***		.23***	.63***	.06*	.31***	.29***	.04	−.03
8. Number of posts	.09**	−.16***	.22***	−.22***	−.15***	.08**	.23***		.27***	.08**	−.02	−.22***	−.02	.04
10. Posts per day	−.31***	−.04	−.24***	−.06*	.20***	.50***	.63***	.27***		.22***	.46***	.40***	.07*	0
11. Mensaje_ presentacion Confidence	−.10**	.05	−.04	.04	0	−.13***	.06*	.08**	.22***		.17***	.25***	−.19***	−.02
12. Slogan Confidence	−.12***	−.02	−.25***	−.02	.17***	.35***	.31***	−.02	.46***	.17***		.13***	.15***	.04
13. Likes/fans	−.19***	.48***	.09**	.48***	.29***	−.02	.29***	−.22***	.40***	.25***	.13***		−.10***	−.12***
14. Slogan polarity	.05	.02	−.07*	.02	.01	.14***	.04	−.02	.07*	−.19***	.15***	−.10***		.24***
15. Post polarity_	−.12***	−.18***	−.13***	−.18***	−.04	.02	−.03	.04	0	−.02	.04	−.12***	.24***	

5.b Point-biserial correlation by categorical variable

Categorical Variable	Polarity	r_ point biserial
Slogan Subjectivity	Presentation Polarity	−.28***
Slogan Subjectivity	Post Polarity	−.19***
Slogan Irony	Slogan Polarity	.09**
Slogan Irony	Post Polarity	.05
Post Agreement	Slogan Polarity	<.001
Post Agreement	Post Polarity	.03
Post Subjectivity	Slogan Polarity	.06*
Post Subjectivity	Post Polarity	−.08***
Post Irony	Slogan Polarity	−.07**
Post Irony	Post Polarity	<.001

Note. Values correspond to Spearman's correlation coefficients (ρ). Statistically significant correlations with significance values, *p < .05, **p < .01, and ***p < .001.
Note. The significance values of the correlations in Table 5 are described as follows: *p < .05, **p < .01, and ***p < .001.

4. Discussion

This discussion interprets the findings in light of platform characteristics, disciplinary differences, and established communication theories. We highlight key patterns of engagement and sentiment, as well as practical implications and methodological contribution and limitations.

4.1. Discussion by social media platform

The differences observed across platforms confirm that digital environments shape not only the format but also the effectiveness of science communication. In line with the Uses and Gratifications Theory (Katz et al., 1974), TikTok, Instagram, and YouTube meet different social needs and attract specific audiences. Our findings show that TikTok fosters high levels of interaction, particularly in the experimental sciences, while Instagram highlights aesthetic style and positive messages. YouTube, although displaying lower interaction metrics, facilitates more detailed explanations, which aligns with the Communication Situation Theory proposed by Bostrom and Heinen (1977).

These results are consistent with previous studies (Zawacki et al., 2023; Gao et al., 2020; Allgaier, 2019), but they also highlight the methodological diversity of research in this field. While much earlier work has relied on surveys or public perception studies, our analysis draws on performance metrics (KPIs), social network analytics, and AI-driven sentiment analysis. This methodological distinction is key, as it shows the need to apply innovative approaches that complement traditional methods, enabling the capture of dynamics specific to algorithm-mediated environments and providing more comparable and replicable results.

Our findings on sentiment partially diverge from earlier research that emphasized a direct relationship between emotional positivity and higher interaction on social media (Gao et al., 2020; Zhu et al., 2020). Moreover, we observed that the effect of affective tone is limited and manifests differently depending on the platform. While Instagram privileges positive messages, TikTok leans towards more objective styles with extreme polarities, and YouTube is characterised by higher subjectivity and irony (Allgaier, 2019). This divergence can be explained through the Uses and Gratifications Theory (Katz et al., 1973, 1974), since each platform responds to distinct audience motivations (brief entertainment on TikTok, aesthetic positivity on Instagram, critical explanations on YouTube). Likewise, discrepancies with some of the literature can also be attributed to methodological differences: whereas previous studies were often based on surveys and self-reported perceptions (Pelger et al., 2016), our study combines performance indicators (KPIs) with automated sentiment analysis, capturing dynamics specific to algorithm-mediated contexts. In this sense, rather than a contradiction, our results suggest that the relationship between sentiment and interaction depends both on platform context and on the methodological approach applied.

4.2. Discussion by field of knowledge

Disciplinary differences also shape communicative impact. Our data show that medicine and physics tend to elicit positive sentiments that drive rapid but superficial dissemination (Tasente & Caratas, 2024), while the social sciences generate more negative or emotionally diverse interactions, often leading to critical debates and substantive comments. These results confirm previous research (Shahzad & Alhoori, 2022; Cortis & Davis, 2020), although they reveal that engineering departs from earlier patterns by achieving unexpectedly high levels of interaction.

This reinforces the value of analysing disciplines in combination rather than in isolation, highlighting how sentiment and engagement interact differently depending on the knowledge domain. Moreover, while many earlier studies have relied on surveys, our KPI-based methodology identifies "performance ceilings" rather than typical averages, thereby offering a complementary perspective. This methodological innovation addresses a key gap: the need for scalable and replicable approaches to compare digital science communication across disciplines.

4.3. Theoretical integration

Beyond descriptive findings, our results can be better understood when situated within established theories. Goffman's Self-Presentation Theory (1959) explains how influencers employ humor, self-disclosure, and closeness to strategically build trust, which may at times replace critical evaluation (Vraga & Bode, 2017). Similarly, Agenda-Setting Theory (McCombs & Shaw, 1972) helps to interpret how hashtags, mentions, and algorithmic amplification determine visibility, creating echo chambers that expand—or restrict—reach (Bouyer et al., 2023; Pearce et al., 2018).

Thus, this study not only documents performance patterns but also contributes to theoretical understanding of how trust, parasocial interaction, and algorithmic design shape science communication in social media environments.

More explicitly, our findings are linked to established communication theories referenced in this paper. Goffman's Self-Presentation Theory (1959) clarifies how trust generated through humor, proximity, and self-disclosure influences the reception of scientific content (Vraga & Bode, 2017; Pennycook et al., 2023). In turn, Agenda-Setting Theory (McCombs & Shaw, 1972) helps to explain how algorithms, hashtags, and viral dynamics configure the visibility of specific scientific topics and condition public attention (Veltri & Atanasova, 2017; Bouyer et al., 2023; Pearce et al., 2018). By situating our findings within this theoretical framework, the study advances understanding of the roles of self-presentation and agenda-setting in determining which scientific issues gain visibility and which remain unseen, while also showing how these theories can be updated and expanded within algorithm-mediated environments.

4.4. Limitations

This study is not without limitations. First, social media trends are inherently dynamic and highly sensitive to cultural shifts, underscoring the need for both longitudinal and cross-sectional approaches to more fully capture this volatile landscape. Second, most prior studies in the social sciences have relied on surveys or public perception methods, which often yield results that diverge from those reported here. This calls for further reflection on how AI-driven algorithms shape user engagement and may differ substantially from broader public sentiment. Third, there is a need to triangulate findings in order to determine the extent to which users freely select content or are subtly guided by algorithmic design. Given that social media platforms are profit-oriented enterprises, their algorithms deliberately prioritize certain posts over others, thereby altering visibility and shaping patterns of engagement. It is therefore essential to distinguish between surface-level metrics, such as "likes," and deeper forms of interaction, such as comments or debates, when assessing communicative impact (see also McCombs & Shaw, 1972, on Agenda-setting theory).

Another limitation concerns the difficulty of quantifying variables such as authenticity, credibility (Hovland & Weiss, 1951), and cultural relevance (Katz et al., 1974), in contrast to more easily measurable indicators such as interaction rates (Shannon & Weaver, 1949). The development of reliable measurement instruments for these more nuanced aspects remains an ongoing challenge.

It is also important to acknowledge that platform algorithms likely influenced the visibility of the analyzed content, which may have affected engagement levels in ways beyond the authors' control. Furthermore, some content was produced in different languages and cultural contexts, raising the possibility of bias in AI-based sentiment analysis tools.

The study focused on prominent science influencers, thereby excluding smaller or less visible communicators, which may limit the generalizability of the findings. Likewise, although engagement metrics such as “likes” and comments are useful indicators, they do not necessarily capture deeper outcomes, such as trust, learning, or long-term social impact. Recognizing this distinction would further enhance the transparency and credibility of the study.

In addition, the focus on top-performing posts introduces a survival bias, as less successful content was excluded from analysis. Temporal restrictions (January 2022–August 2023) also constrain the generalizability of the results to other periods, given the rapid evolution of digital platforms and user behaviors.

Despite these limitations, the study presents several strengths that warrant emphasis. It is novel in its comparative analysis across multiple platforms, it draws upon a large and diverse dataset (1200 posts across five disciplines), and it adopts an interdisciplinary approach that combines sentiment analysis with communication theory. The use of AI-driven sentiment analysis tools and the focus on real-world digital environments provide both methodological innovation and practical relevance, particularly in the context of combating digital misinformation. Highlighting these strengths will help to underscore the value and impact of this research while advancing the field.

4.5. Practical applications

This study outlines a set of practical recommendations intended for science influencers engaged in digital science communication on social media.

4.5.1. Guidelines by social media platform

TikTok: Effective science communication on TikTok requires short, visually dynamic formats that capture user attention rapidly. Posts should prioritize high interaction metrics (e.g., likes and reactions) while maintaining objective language and avoiding excessive subjectivity. The platform favors user interaction prompts, as it is designed to facilitate active engagement. Emotional appeals, however, have little measurable effect on engagement. Moreover, brevity is essential, as longer posts diminish emotional intensity and overall impact.

Instagram: Instagram offers a hybrid format that combines visual and emotional dimensions, making it particularly effective for inspirational or aesthetic topics. Messages framed with positive sentiment and moderate subjectivity tend to yield stronger impact. Incorporating trending hashtags and emotionally charged keywords further enhances visibility. Shorter descriptions foster higher emotional resonance, while humor and personal storytelling are valuable for fostering a sense of proximity with audiences.

YouTube: Unlike TikTok or Instagram, YouTube does not consistently perform well in terms of active interaction (likes or comments). Instead, it functions more effectively as a repository for structured, explanatory content. Irony and emotional diversity can enhance content appeal, but excessively long posts reduce their emotional impact. Consequently, YouTube is better positioned as an educational resource than as a channel for viral dissemination.

4.5.2. Guidelines by scientific knowledge area

Engineering: Communication in engineering benefits most from explanatory visual content, as this field records the highest levels of engagement through likes. Interaction remains predominantly one-directional; therefore, generating comments should not be the primary focus. Messaging should employ a positive and objective tone, with platforms such as YouTube and TikTok offering the greatest effectiveness. Emotionally charged narratives should be avoided, as clarity and data-driven presentation are paramount.

Experimental Sciences: For the experimental sciences, content that combines positive sentiment with higher levels of subjectivity is most effective. Humor and irony, when used moderately, can enhance audience reception. Instagram and TikTok provide optimal reach, while message length should remain short to preserve emotional intensity and prevent audience disengagement.

Social Sciences: In the social sciences, fostering dialogue is more important than maximizing likes. Effective strategies include addressing controversial or emotionally resonant topics, such as human rights or psychology, which can stimulate debate. Formats that encourage discussion (e.g., dilemmas or open-ended questions) are recommended. Incorporating subjective perspectives further enhances engagement, with Instagram and TikTok serving as the most effective platforms for socially oriented communication.

Health Sciences: Effective communication in the health sciences hinges on emotionally resonant messages with positive sentiment. Combining factual information with personal testimony enhances credibility and relatability. TikTok and Instagram offer the strongest potential for reach and interaction. Posts should remain concise, direct, and emotionally compelling.

Arts and Humanities: In the arts and humanities, emotionally charged and subjective messaging drives engagement. Irony, critique, and reflective formats are particularly effective, especially when combined with visual or audio elements that convey emotional nuance. Posts should be brief yet thought-provoking, with TikTok and Instagram serving as the preferred platforms.

4.5.3. Methodological innovations

In addition to their immediate utility as practical guidelines, these findings highlight the methodological innovations and counterintuitive results that emerged from the analysis. Such contributions represent key advances in the scholarly understanding of digital science communication, opening avenues for refining theoretical frameworks and challenging established assumptions about how scientific content circulates and resonates in online environments.

5. Conclusion

In summary, science communication on TikTok, Instagram, and YouTube represents a dynamic field that requires a comprehensive understanding of success indicators, differential behaviors across platforms and knowledge domains, and the broader context of user interaction. The application of communication theories provides a robust conceptual framework for analyzing and optimizing science dissemination on these platforms.

A key aspect is that science influencers can enhance the practical impact of their work by tailoring content to the specific characteristics and audiences of each platform. At the same time, broad generalizations should be avoided: findings must be interpreted within the context of the influencers and content types analyzed. Our results indicate that platform choice and content type play a more decisive role than emotional sentiment in shaping engagement, providing a clear and actionable message for practitioners.

Significant correlations between engagement measures (interaction rate, likes/followers) and emotional or content-related variables (message polarity, conveyed trust) suggest that not only the volume of interactions, but also the expressive and affective quality of messages, influences audience response. Digital engagement does not depend solely on the quantity of posts, but on how messages are formulated and the emotional weight they carry, providing added value to the analysis of communicative impact.

Finally, it is essential to recognize the mediating role of algorithms, which not only influence visibility but also actively shape interaction patterns. Considering algorithmic dynamics, alongside content design and platform-specific characteristics, will be crucial for both future research and the development of effective, evidence-based strategies in digital science communication.

CRediT authorship contribution statement

Montserrat Aiger: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Carmen Elboj:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Raquel Lozano-Blasco:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Marian Acero-Ferrero:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the author(s) used ChatGPT (OpenAI, 2025) in order to improve the visualization of some of the graphic material.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2025.108866.

Data availability

Data will be made available on request.

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