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Authenticity and Emotion in the Discourse of Female Influencers on Mental Health on Instagram

Autenticidad y emoción en el discurso sobre salud mental de mujeres influencers en Instagram

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Abstract: This study explores how authenticity and emotional tone shape audience responses to mental health disclosures by female Spanish influencers on Instagram. Using Artificial Intelligence and Natural Language Processing tools, 13,407 user comments were analyzed to classify emotions into six categories: admiration, empathy, anger, sadness, neutrality, and gratitude. Descriptive and correspondence analyses identified dominant emotional patterns and their associations with post types—personal, unrelated, or promotional. Results show that authentic self-disclosures generate predominantly positive emotions (admiration and empathy), whereas negative reactions (anger and mockery) are linked to promotional content. Authenticity and coherence between text and image emerged as key elements fostering user engagement. These findings contribute to understanding emotional dynamics in digital communication on mental health and highlight the potential of AI tools to analyze public discourse online.

Keywords: Social Media; Mental Health; Influencers; Emotions; Artificial Intelligence; Natural Language Processing.

Resumen: Este estudio analiza cómo la autenticidad y el tono emocional influyen en las reacciones del público ante las revelaciones sobre salud mental de influencers españolas en Instagram. Mediante herramientas de Inteligencia Artificial y Procesamiento del Lenguaje Natural, se analizaron 13.407 comentarios de usuarios para clasificar las emociones en seis categorías: admiración, empatía, enfado, tristeza, neutralidad y gratitud. Los análisis descriptivos y de correspondencias identificaron los patrones emocionales dominantes y su relación con los tipos de publicaciones —personales, no relacionadas o promocionales—. Los resultados muestran que las revelaciones auténticas generan principalmente emociones positivas (admiración y empatía), mientras que las negativas (enfado y burla) se asocian con contenidos promocionales. La autenticidad y la coherencia entre texto e imagen se consolidan como factores clave de la implicación del público. Los hallazgos contribuyen a comprender la dinámica emocional en la comunicación digital sobre salud mental.

Palabras clave: redes sociales; salud mental; influencers; emociones; inteligencia artificial; procesamiento del lenguaje natural.

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1. Introduction

The rise in mental health issues is a major societal challenge, exacerbated by the COVID-19 pandemic, with studies reporting increased anxiety and depression in women (Sun *et al.*, 2023). In Spain, mental health concerns are growing, with 34% of respondents reporting issues compared to 26% in *Switzerland* (Fundación AXA, 2024), and around 40% rating their mental health negatively (Confederación Salud Mental España y Mutua Madrileña, 2023).

Young people are particularly affected (Benton *et al.*, 2024), prompting a <<National Mental Health Emergency>> declaration in 2021. Simultaneously, social networks (SNs) have become integral to communication, with nearly 5 billion users worldwide by 2024. In Spain, 90% of individuals aged 16–24 and 85% of those aged 25–34 use SNs, with Instagram (24 million users) and TikTok (16.74 million users over 18) being among the most popular (Datareportal, 2024). With this digital shift, mental health content on SNs has surged, as celebrities and influencers openly discuss their struggles. This trend has been linked to increased public awareness (Lee *et al.*, 2021), fostering empathy (Withers *et al.*, 2021), reducing disparities (Pendleton, 2023), and encouraging open dialogue (Francis, 2021). However, celebrity admiration may correlate with poor mental health, particularly in women and youth (Zsila *et al.*, 2021), and some argue it reinforces neoliberal self-care narratives (Franssen, 2019). Additionally, Gronholm & Thornicroft (2022) highlight the complexity of achieving real attitudinal and behavioural changes through celebrity influence.

Previous research on mental health discourse in social media has shown that online self-disclosure tends to promote empathy, social connection, and stigma reduction (Luo & Hancock, 2020; Lee *et al.*, 2021; Withers *et al.*, 2021). However, the emotional impact of such content strongly depends on who communicates it and for what purpose. In this regard, studies on celebrity and influencer communication suggest that authenticity plays a key role in how audiences interpret messages, while commercial or self-promotional intent can reduce credibility and even trigger negative reactions (Franssen, 2019; Zsila *et al.*, 2021; Gronholm & Thornicroft, 2022). At the same time, advances in Artificial Intelligence (AI) and Natural Language Processing (NLP) have made it possible to analyze large-scale emotional patterns in digital communication. Most of these studies, however, have focused on Twitter rather than visually oriented platforms such as Instagram, where image–text coherence and authenticity may be even more relevant (Oscar *et al.*, 2017;

Budenz *et al.*, 2020; Tudehope *et al.*, 2024). Despite this growing body of research, no previous study has examined emotional responses to influencers' mental health disclosures on Instagram using AI-based emotion detection techniques. The present study addresses this gap by exploring how emotional reactions vary according to the type and authenticity of mental health posts shared by Spanish influencers.

Building on this gap, the present study aims to explore the emotional reactions elicited by Instagram posts in which Spanish influencers disclose experiences related to mental health. Using Artificial Intelligence tools based on NLP, we analyze audience comments to better understand how authenticity and visual coherence shape emotional engagement.

1.1. Digital Health Communication and Self-disclosure

In recent years, the role of influencers in promoting mental health has gained increasing relevance, as they act as mediators between scientific information and digital audiences. As Sánchez Castillo *et al.* (2025) point out, their presence in the digital sphere helps to spread messages of awareness and emotional support, bringing mental health to a wider and more diverse public.

Influencers have also helped raise awareness about specific diseases by sharing personal experiences on social media. In the case of epilepsy, Ibáñez-Hernández & Carretón-Ballester (2025) demonstrate that, although influencer patients are a minority on Instagram, their testimonials and reach help to normalize and raise awareness of the illness, which contributes to breaking stereotypes and reducing stigma.

The increasing visibility of mental health issues in digital spaces transforms the ways in which people communicate their experiences of vulnerability, recovery, and care. Platforms such as Instagram have become privileged spaces for the public circulation of discourse on mental health, where influencers who share personal narratives that combine authenticity, emotion, and social engagement play a key transformative role (Adeane & Stasiak, 2024; López-de-Ayala & Antonio Díaz-Lucena, 2025).

The act of sharing one's own experience in the field of mental health (conceptualised as disclosure of personal information) plays a fundamental role in generating empathy and perceived credibility. Previous studies show that revealing personal information increases message acceptance and emotional engagement, especially when it is perceived as spontaneous and authentic (Zhang *et al.*, 2025). However, this visibility is ambivalent: while it promotes awareness and destigmatization, it can also contribute to the commodification of mental health as part of the influencer's personal brand, generating tensions between privacy and promotion (Baquerizo-Neira *et al.*, 2025; Sánchez Castillo *et al.*, 2025).

From a communication perspective, these tensions demonstrate how affective expressions are intertwined with the logic of platforms, where algorithms reward measurable interactions (likes, comments, shares). In this sense, emotional discourse functions both as a form of social support and a resource for visibility, placing digital narratives about mental health at the intersection of care and consumption.

1.2. Authenticity and Mediated Self in Influencer Culture

Authenticity has become a central concept in the study of digital communication, used as an indicator of credibility, trust, and intimacy between content creators and their audience. In influencer culture, authenticity is more of a performance than an innate quality: it is constructed and negotiated through stylistic, linguistic, and emotional cues that the audience interprets as <<reality>>. Its value lies not so much in being authentic as in appearing to be so in a media environment that rewards selective transparency and emotional engagement (Marwick, 2015).

Research on mediated authenticity shows that users evaluate the truthfulness of content based on consistency between verbal, visual, and emotional cues, such that even slight discrepancies can lead to perceptions of manipulation, while congruence fosters empathy and solidarity (Audrezet *et al.*, 2020). When influencers address sensitive topics such as mental health, even minor discrepancies between the tone of the text and the image can generate perceptions of inauthenticity or exploitation. Conversely, emotional congruence tends to foster empathy and solidarity (Marwick, 2015).

Thus, communicative authenticity involves a delicate balance between self-disclosure and image control, between emotion and professionalism, between vulnerability and competence. The ability to convey an <<authentic>> emotion is a strategic communication skill and a form of symbolic capital. For followers, affective resonance acts as a sign of sincerity and reliability, strengthening the social bond with the influencer.

As Garaycoa *et al.* (2024) point out, some influencers publicly manage emotions such as anxiety or sadness and articulate a discourse of empowerment, while their visibility is mediated by the algorithms and aesthetics of the platforms, which determine which forms of vulnerability achieve greater social validation.

1.3. Emotional Communication and Affective Publics

The emergence of what Papacharissi (2014) calls affective publics (communities organized around shared emotional expressions) highlights the central role of emotion in digital culture. On social media, emotions circulate rapidly through posts, comments, and emojis, shaping a collective emotional climate that reinforces a sense of belonging and commitment (Pérez-Castaños *et al.*, 2023; Cervantes Olivera, 2025). In health communication contexts, this affective participation can foster empathy and support, but it can also amplify moral judgments or stigmas depending on the dominant tone of the conversation.

From the perspective of communication theory, emotions are increasingly understood as discursive and relational practices, rather than simply psychological states. Emotional tone becomes a linguistic and social resource that structures the interaction between influencers and followers. Research on emotional contagion and engagement (Berger & Milkman, 2012; Al-Rawi, 2017) indicates that positive emotions—such as admiration, joy, or empathy—promote the dissemination and acceptance of messages, while negative emotions—such as anger or contempt—increase visibility through controversy. In the field of health, positive emotions are often associated with hope and collective support, while negative emotions may reflect scepticism or fatigue in the face of overexposed narratives. Analyzing the emotional valence of comments (positive, neutral, or negative) allows us to understand the resonance of the message and the perception of its authenticity.

1.4. Artificial Intelligence (AI) and Discourse Analysis in Digital Media Research

The incorporation of Artificial Intelligence (AI) and Natural Language Processing (NLP) into communication research has opened new possibilities for large-scale discourse analysis. These tools allow for the systematic classification of emotional expressions and linguistic patterns in large volumes of data, complementing traditional interpretive methodologies (Alhussein *et al.*, 2025).

In this study, AI is not conceived as a substitute for, but rather as an extension of, communicative analysis (Lindgren, 2025). The use of emotion detection models—in this case, RoBERTuito[1], specialized in Spanish—allow us to identify affective nuances in user comments that would be difficult to capture manually. However, the validity of the results depends on their contextual and theoretical interpretation, rooted in the cultural understanding of discourse (van Dijk, 2016).

[1] The language model used was RoBERTuito (Fine-tuned BERT model for Spanish, 28 Feb 2023) [Language Model]. https://github.com/PlanTL-GOB-ES/robertuito

This approach falls within the emerging field of computational communication science (Arcila-Calderón *et al.*, 2021), which seeks to integrate algorithmic tools with socio-theoretical frameworks. In the study of digital discourses on mental health, automated emotion analysis allows us to observe patterns of empathy, irony, or resistance that reveal how audiences negotiate meaning and authenticity.

Furthermore, this methodological approach invites reflection on the role of technology in shaping discourse. Algorithms not only analyze emotions, but also modulate their visibility, determining which affective expressions are amplified and which remain invisible. Therefore, analyzing emotional reactions using AI is both an analytical and critical exercise: it enables us to unravel the communicative structures and power dynamics that govern digital interaction.

Emotional engagement is therefore conceived as a communicative exchange in which meaning, emotion, and credibility are jointly constructed. The analytical focus is shifting from isolated content to the affective infrastructures of communication—that is, how language, image, and algorithms shape the emotional lives of digital audiences. Consequently, the use of AI tools for emotional analysis is not limited to a technical purpose but is part of broader research on the mediation of feelings in digital culture. Understanding these dynamics contributes to the debate on ethical communication in health, the responsibility of influencers and the algorithmic governance of empathy.

Based on this framework, the study addresses the following research questions (RQ):

RQ1. What are the predominant emotional reactions to mental health disclosures shared by Spanish influencers on Instagram?

RQ2. How do these emotional reactions vary according to the type of post (personal disclosure, unrelated content, or promotional)?

RQ3. To what extent does the visual coherence between text and image predict the emotional tone of user responses?

We hypothesized that posts featuring authentic self-disclosure would elicit more positive emotions (e.g., love, empathy, gratitude), whereas promotional posts would evoke more negative emotions (e.g., anger, mockery).

2. Method

2.1. Procedure

AI algorithms based on NLP (Natural Language Processing) and ML (Machine Learning) were modelled and applied to detect emotions in the comments to posts of Spanish influencers who made some self-disclosure about mental health problems on Instagram.

Detected emotions were classified into love/admiration, comprehension/empathy, anger/mockery, sadness, neutrality, and gratitude. A brief outline of the emotions considered is as follows: (a) Love and admiration: messages that express deep affection, respect, and recognition. <<Amazing, you're such an inspiration to all of us! >>; (b) Empathy/comprehension/identification: comments that reflect an interest in and understanding of the message, including situations of self-identification with the context or putting oneself in the other person's place. <<I totally get you; I've gone through something similar, and I really relate to your experience. >> (c) Sadness: this primary emotion (Ekman, 2003) arises from difficult events and denotes a sense of heaviness. It includes expressions of sympathy for the person. <<That's so tough... I hope you start to feel better soon. >> (d) Anger/contempt/mockery: this category includes responses of frustration and even criticism toward the person, perceiving them as insincere or superficial. <<Everything's just a show>>; (e) Neutral: some messages lack enough context to assign a specific label. <<What's happened? >>; (f) Gratitude: these messages convey sincere appreciation for discussing mental health topics on social media. <<Thank you for all you do. >>

It should be noted that detecting sarcasm related to anger, indignation, and mockery can be particularly difficult, so special attention was paid to this phenomenon. For example, <<Taking photos of you crying is great>> might seem like a positive comment, although it is clearly sarcastic and is classified as <<anger>>. On the other hand, initially, when we began categorizing, we included all comments of love/admiration and empathy in the same <<positive>> category. However, we consider it necessary to clarify the differences between love/admiration, where it is possible to find more generic comments that do not really seem to be related to the message. For example, responding to the disclosure of a mental health problem with <<you are beautiful>> or <<we love you>> is not negative, but it does not seem to generate an empathetic response or genuine concern and support. However, in comments expressing empathy or understanding, a greater connection was identified, incorporating personal experiences in many cases and observing a genuine response, for example <<How necessary it is to show these things too. Congratulations and thank you for making us see that we all have bad days, months or periods. >>.

In our research, we applied a methodology based on supervised machine learning using classification algorithms, including Random Forest, Deep Learning, and BERT (Bidirectional Encoder Representations from Transformers). We developed a labelled corpus containing emotional categories based on comments from Instagram posts where celebrities disclosed mental health experiences. This corpus was used to train the AI models with categorized messages. Two independent psychologists annotated the dataset according to a detailed guide, and a third expert reviewed and resolved any discrepancies, ensuring accuracy. With a low disagreement rate of 7.82%, the categorization process demonstrated strong consistency.

Specifically, for the analysis carried out in this article, we selected a model based on BERT, called RoBERTuito. It is a linguistic model designed for social media texts in Spanish, based on RoBERTa and trained on 500 million tweets (Pérez et al., 2022). This model outperforms other Spanish models such as BETO, BERTin, and RoBERTa-BNE. In fact, RoBERTuito demonstrated optimal accuracy in emotion classification, with accuracy scores between 93% and 83.7% (Merayo et al., 2024). Morevover, RoBERTuito shows a recall that varies between 87.8% for Sadness and 95.0% for Love/Admiration, showing that the model identifies emotions more effectively. Meanwhile, the F1-score ranges from 85.1% (Sadness) to 94.0% (Love/Admiration), reflecting a balanced performance between precision and recall. These promising results support the potential for advanced ML tools to accurately monitor emotional responses to mental health discussions on social media in real time.

For this study, a search was conducted for more posts in which Spanish influencers discussed or revealed their mental health issues on Instagram. The selection of posts was based on their content, i.e., focused on describing mental health problems experienced or revealing personal diagnoses. However, once the search was completed to avoid the inclusion of new aspects related to social response, posts that met the following inclusion criteria were selected. The inclusion criteria were: a) the post had to be made directly by the author and be related to mental health (include a disclosure of problems or description of symptomatology); b) the post had to be written in Spanish and be made by a Spanish well-known person (influencer, celebrity or famous); c) the person had to have more than 100,000 followers on their Instagram profile. After a search of the social media posts, we only found a couple of posts by the same man that met these requirements, so to avoid gender bias we included criterion f) the post had to be made by a woman. The search was carried out during the months of September and February 2023, including up to 5 years of social media posts.

These inclusion criteria were established because we considered that very different profiles were likely to generate totally different responses that would correspond to a different categorization system. For example, profiles with very few followers who post about mental health and reveal their diagnoses, even if they are public and open profiles, tend to receive comments only from close friends or acquaintances, who, as a rule and due to social convention, are supportive, thus deviating from the objective of our study, which is to understand the social response on a large scale. The decision to include only women was made because intersectional stigma can affect the social response in men (e.g., <<men don't cry>>), requiring a different categorisation. In addition, it was also decided to eliminate cultural aspects other than Spanish or Latin American culture, preferring not to include languages other than Spanish.

2.2. Sample

Once these inclusion criteria were established, the 10 posts that met them came from six different influencers. All of them are content creators, famous for their activity on social media, although one of them (Tania Llasera) started out as a television presenter and another (Tamara Gorro) became famous after participating in a television contest. All of them belong to the fashion and/or television sector in Spain, with a similar target audience, the adult population in general or young adults.

Table 1 provides a detailed description of the 10 Instagram posts analysed, created by six different Spanish celebrities or influencers, whose posts were classified into three categories: (1) contains posts with text and unrelated images or videos, where a diagnosis was disclosed but accompanied by unrelated visuals, such as the author posing in various locations, which includes 7 posts and accounts for 51.9% of the comments analyzed; (2) contains posts with text and images or videos directly related to mental health, where authors spoke openly about their issues, often addressing the camera directly or sharing images of themselves in a neutral or emotional state (e.g., crying), comprising 2 posts and representing 46.8% of the comments; (3) contains posts with text and images or videos about mental health intended for promotional purposes, aimed at selling a product or service (promotional video marketing), with 1 post making up 1.3% of the comments.

All posts included in the dataset addressed mental health in some way, as influencers referred to their own emotional or psychological state (e.g., anxiety, depression, burnout). However, the main distinction between categories lies in the communicative intent and the coherence between the written message and the accompanying visuals. Thus, even <<unrelated>> or <<promotional>> posts were part of the same corpus of mental health disclosures: in these cases, influencers mentioned feeling unwell or struggling with mental health issues while simultaneously sharing aesthetic content or promoting products or services (e.g., beauty items, wellness clinics). This internal categorization allowed for comparing audience reactions according to the tone and purpose of the disclosure, while ensuring that all posts remained within the domain of mental health communication.

Table 1. *Description of the posts, type of post, frequencies of comments and percentages.*

Author	Type of publication	Comments	Percentage
Dulceida 1	Image or video not related to mental health	1905	14.4
Laura Escanes	Image or video not related to mental health	825	6.2
Tamara Gorro 1	Image or video not related to mental health	1591	12.0
Tamara Gorro 1	Image or video not related to mental health	1591	12.0
Tamara Gorro 2	Image or video not related to mental health	510	3.9
Tamara Gorro 3	Image or video not related to mental health	1554	11.7
Tania Llasera	Image or video not related to mental health	489	3.7
Marta Pombo	Image or video related to mental health	4459	33.7
Dulceida 2	Image or video related to mental health	1733	13.1
Marina Rivers	Promotional Video Marketing	171	1.3
Total		**13237**	**100.0**

Source: prepared by the authors.

Initially, 21,151 comments were obtained, but the database was processed and reduced with these criteria: a) those comments that were not made in Spanish were eliminated; b) those that contained emoticons were eliminated. In the comments that contained emoticons and text, the text was maintained, eliminating the emoticon to avoid conditioning the labelling; c) comments that contained only acronyms or were incomprehensible in their wording were eliminated. Finally, 13,407 comments were selected from these posts to be analysed using our automatic learning algorithm (based on BERT) to detect the emotions of these comments.

2.3. Data Analysis

The data analysis involved several steps to examine the distribution of emotions and their relationship to types of posts on social media. First, descriptive frequency analyses were conducted to identify the prevalence of each emotional category, providing an overview of the most common emotions in response to posts about mental health issues of Spanish influencers.

This frequency analysis offered initial insights into the dominant emotional reactions within the dataset. Subsequently, a correspondence analysis was conducted to explore and visually represent the associations between specific emotions and types of posts (e.g., promotional vs. personal mental health disclosures). Correspondence analysis is a multivariate statistical technique that aims to represent the relationships between categorical variables in a graphical format, making it easier to interpret complex data. This analysis produces a two-dimensional space in which the proximity between points reflects the strength of the association between variables. The concept of <<inertia>> in correspondence analysis refers to the amount of variance explained by each dimension. Inertia is calculated for each dimension, and the total inertia represents the total variance explained by the model. The higher the inertia, the more significant the dimension is in explaining the relationships between the variables.

This analysis enabled the mapping of relationships between variables in a two-dimensional space, revealing patterns, for example, anger and mockery were frequently associated with promotional posts, while love and admiration were more often linked to genuine personal disclosures. Finally, Chi-square tests (Connelly, 2019) were performed to assess the statistical significance of these observed relationships, confirming that the associations between post types and emotional responses were not attributable to chance. These analyses were designed to test the study's hypotheses about the relationship between post type and the emotional reactions they elicit. Specifically, it was expected that posts revealing personal information would be associated with more positive emotions (love, empathy, gratitude), while promotional posts would be associated with higher levels of anger and mockery. The analyses were performed using SPSS-29 software, with a significance level of alpha = 0.05, ensuring robust and reliable results.

3. Results

3.1. Emotions Found in the Comments

Consistent with RQ1 and our first hypothesis, the most common emotion found is love/admiration (Figure 1), which appears in 8,995 comments, representing

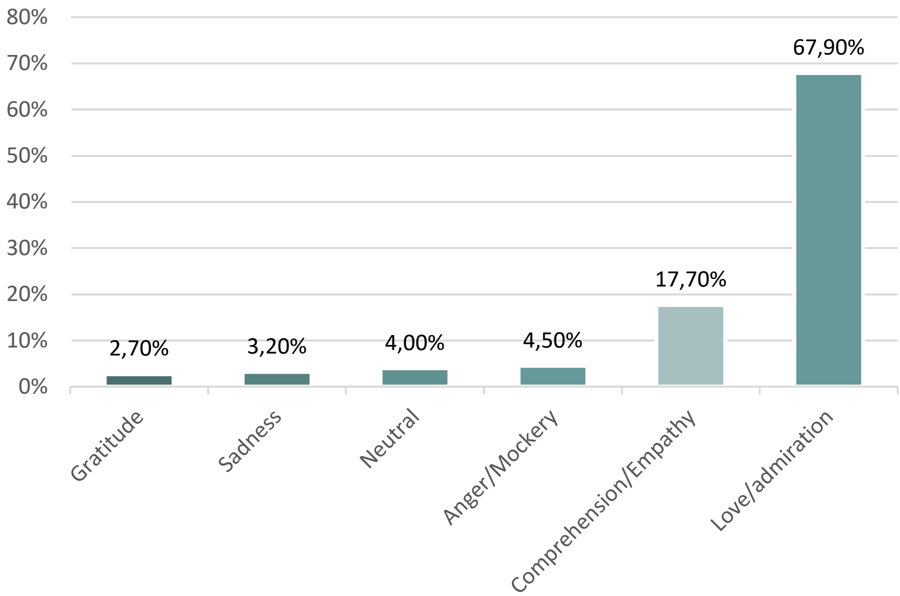
68.0% of the total. Many messages of love or admiration consisted of short expressions of affection and encouragement such as <<beautiful, >> <<keep going, you can do it, >> and <<we love you>> while others were more elaborate: <<When you're not feeling well, it's necessary to STOP and reconnect with yourself... We are sure you will get through this. >> <<You come first, beautiful, above all else, and all of us who love you will always support you; you are wonderful, and you will overcome all of this>>.

The next more common emotion is comprehension/empathy, with 2,347 mentions, representing the 17.7% of the total. Empathetic comments typically imply that the person understands and has put themselves in someone else's shoes, sometimes including personal revelations about mental health, such as <<we all go through moments like this, >> or <<I understand so much... I hope this new year brings us more health and more opportunities. I want to get out of this depression>>.

Negative emotions such as anger/mockery and sadness are less frequent, with 591 comments (4.5%) and 420 (3.2%), respectively. This kind of comments imply rejection and disdain for the person, such as <<posting a photo crying is a whole new level of wanting attention and ridiculousness, >> or <<You have a moment of anxiety and feeling bad, and the only thing that crosses your mind is to take photos? Oh my, you don't have a bad moment... what you have is a problem in your head.>> Meanwhile, comments expressing sadness convey feelings of pity toward the person, such as <<poor thing>>.

Neutral emotion account for 4.0% (528 comments), and finally, gratitude appears in 356 comments, constituting 2.7% of the total. These comments convey appreciation and encouragement, often expressing thanks for the openness or bravery of sharing personal experiences. Examples include, <<Thank you for sharing this; it really helps me feel less alone>>, <<Your strength gives me hope, >> or <<Seeing you speak up about this reminds me I'm not the only one. Thanks for being so real. >> Other comments included aseptic advice that, while they may show support or love, could be applied to practically any experience, such as <<do what you feel like>> or <<God bless them. >>

Figure 1. *Descriptive Statistics by Frequencies of the Emotion Variable*



Source: prepared by the authors.

3.2. Relationship between Emotions and Type of Post

In line with RQ2 and our second hypothesis, Table 2 shows that in posts unrelated to mental health, the predominant emotion is love/admiration (4,171 comments), followed by comprehension/empathy (1,668 comments), with less presence of negative emotions such as anger/mockery (314 comments) and sadness (219 comments). In posts related to mental health, there is an increase in the frequency of love/admiration (4,790 comments) and comprehension/empathy (674 comments), as well as a higher proportion of gratitude (223 instances) compared to other types of posts. As hypothesized, promotional marketing videos show a greater proportion of negative emotions, especially anger/mockery (105 instances), while positive emotions such as love/admiration (34 instances) and understanding/empathy (5 instances) are less frequent.

Table 2. *Cross Tabulation of the Emotion Variable and the Type of Publication Variable.*

	Image or video not related to mental health	Image or video related to mental health	Promotional video marketing	Total
Comprehension/Empathy	1668	674	5	2347
Love/admiration	4171	4790	34	8995
Anger/Mockery	314	172	105	591
Sadness	219	200	1	420
Neutral	369	133	26	528
Gratitude	133	223	0	356
Total	**6874**	**6192**	**171**	**13237**

Source: prepared by the authors.

The correspondence analysis shows a two-dimensional model in which the first dimension had an inertia of $\lambda 1 = 0.11$, corresponding to an explained inertia proportion of 73.7%, and the second dimension had an inertia of $\lambda 2 = 0.04$, with an explained inertia proportion of 26.3%. The sum of the factorial inertias contributed to a total inertia of $\varphi 2 = 0.15$, a statistically significant value in the Chi-Squared test ($X2 = 2005.26$; $p = 0.000$). Together, these two dimensions explain 100% of the variance, as the cumulative proportion of accounted inertia reaches 100%. This suggests that the two-dimensional model fully captures the relationship between emotions and the types of posts in the analyzed comments.

Regarding the emotions, anger/mocking contributed significantly to dimension 1, while comprehension/empathy contributed to dimension 2, followed by love/admiration. Neutral or gratitude emotions contributed to dimension 2 to a lesser extent, and sadness did not contribute to either dimension. And regarding post type, image or video posts related and unrelated to mental health contributed significantly to dimension 2, while promotional marketing posts contributed primarily to dimension 1. The distribution of emotions and types of posts in the two-dimensional model allows for a clear understanding of how these factors interact and influence each other. This configuration also provides partial evidence for RQ3, suggesting that visual-text coherence influences the emotional tone of responses, particularly the prevalence of gratitude and love when image and text are congruent. The associations between the emotions and posts are represented visually in Figure 2, where emotions such as anger/mockery are located closer to promotional posts, while love/admiration is positioned closer to personal disclosures. The relative contribution of each emotion and the type of comment to each dimension is shown in Table 3.

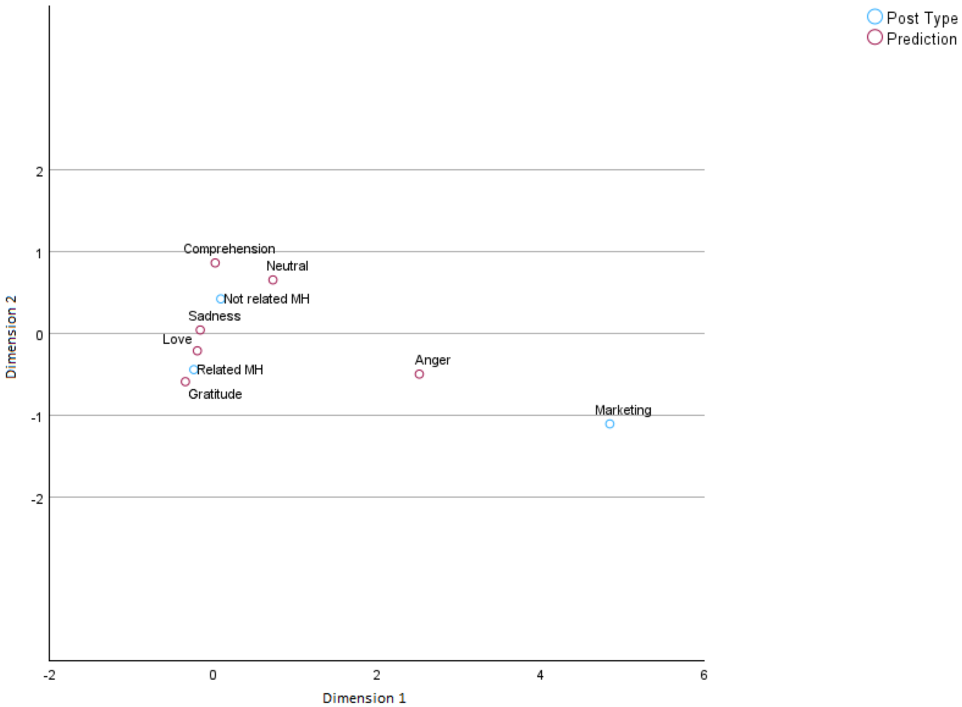
Table 3. *Correspondence Analysis: Relationship between Emotions and Types of Posts in Social Media Comments.*

	Dimension 1	Dimension 2	Inertia Total	Contribution to Dimension 1	Contribution to Dimension 2
Emotion					
Anger/Mockery	2.519	-.495	.097	.848	.055
Comprehension/ Empathy	.024	.864	.026	.000	.662
Love/admiration	-.194	-.210	.015	.076	.150
Sadness	-.158	.044	.000	.002	.000
Neutral	.730	.656	.011	.064	.086
Gratitude	-.340	-.587	.003	.009	.046
Type of publication					
Image or video not related to mental health	.093	.424	.020	.013	.467
Image or video related to mental health	-.237	-.440	.027	.078	.454
Promotional video marketing	4.846	-1.104	.104	.908	.079

Source: prepared by the authors.

Figure 2 visually presents the associations between the types of posts and the emotions expressed in the comments, as detailed in the previous tables. The emotions of anger and mockery are found to be more closely associated with posts that use mental health for commercial purposes (marketing), while other emotions are linked to posts that primarily focus on personal revelations. Furthermore, it can be noted that emotions of comprehension or neutrality are more prevalent in posts where the content, in addition to discussing mental health, includes unrelated images or videos. This finding further supports RQ3, indicating that greater visual-text coherence enhances the prevalence of positive emotional responses such as love and gratitude. In contrast, when the text aligns with the accompanying images or videos, emotions of love and gratitude tend to dominate. The emotion of sadness appears to be equidistant from both types of posts.

Figure 2. *Correspondence Analysis: Relationship between Types of Posts and Emotions in Social Media Comments.*



Source: prepared by the authors.

4. Discussion

This research is the first to analyze, through AI, the emotional response of society to Instagram posts focused on the revelation or discussion of mental health issues made by Spanish female influencers.

Addressing RQ1, the results show that the posts from celebrities or influencers are made in different ways. One type of post involves accompanying the written post with photos or videos that are unrelated to its content. This was the main style found in most of the posts in this study, where the text about mental health was usually accompanied by a set of images that were only loosely related, consisting of pictures of food, idyllic landscapes, or posed shots with different types of clothing or makeup. Another type of format features images or videos related to the content accompanying the written post. Here, a smaller number of posts were found, and the images typically consisted of the person crying or looking sadly at the camera, or videos in which they spoke in the first person about their problems. Finally, another type of post involves the influencer attempting to promote or sell something by using mental health as a motivating factor. In the case of the post included in the study, it is a video promoting makeup to feel good instead of experiencing anxiety/depression.

These results provide insight into the treatment of mental health on social media in recent years in Spanish. Although there is an increase in content related to mental health, and many celebrities are <<coming out of the closet>> by discussing their mental health issues, in most cases, these discourses do not delve deeply into health problems or offer useful information to the user. Instead, they are used as just another post to <<to gain likes>> and share aspects of their lives accompanied by idyllic images (unattainable for the average citizen), or, in the worst cases, used for commercial purposes. This is consistent with other critical studies on the use of mental health in social networks, such as Franssen (2019), and the negative outcomes associated with poorer mental health found in young people who admire celebrities (Zsila *et al.*, 2021).

In response to RQ2 and consistent with our main hypothesis, the primary emotions identified are love and admiration (68%), followed by comprehension and empathy (17.7%), suggesting that the overall social response is positive. These results are coherent with previous research that points out the benefits of sharing and talking in SNs about mental health. The study by Luo and Hancock (2020), reviewed social media users who shared mental health revelations, suggesting that these disclosures are beneficial for individuals experiencing psychological distress, as they provide psychological resources and tend to be well received by the general public. Additionally, other authors have noted that, in general, the impact of posts about mental health promotes empathy and acceptance (Nelson, 2019; Withers et al., 2021). Most people respond to the revelation with love or even admiration, and more importantly, empathy. In the empathetic comments, in many cases, in addition to putting themselves in the other person's shoes, many SNs users talk about their own mental health problems, encouraging dialogue on this topic and generating support networks. This may reflect the impact of the new mental health strategies implemented in Spain during the period 2022-2026, which aim to fight stigma and improve the approach to mental health by the Spanish community at large (Bernal-Delgado *et al.*, 2024), as well as underlining the importance of virtual environments as resources for support and support.

A smaller number of negative emotions, such as anger/mocking (4.5%) and sadness (3.2%), were also found, however, it is relevant to note their existence. This notably low percentage is surprising, given that influencers are highly visible on social media, making them vulnerable to online harassment and hate (Mardon *et al.*, 2023; Ouvrein, 2025). The review by Valenzuela-García *et al.*, (2023) found that more than 70% of Spanish influencers have experienced some form of online harassment and toxic criticism. It is known that these influencers have experienced such negativity in these posts, but to a lesser extent than positive messages. Finally, gratitude has a small presence compared to other emotions (2.7%). It is known that gratitude increases feelings of social connection and support (Chang *et al.*, 2012), making this type of messaging useful for strengthening the influencers' connection with their followers, as well as generating an atmosphere of understanding, which is perhaps the most difficult emotion to evoke.

In relation to RQ3, the relationship between the emotions generated and the type of post shows interesting connections. Posts accompanied by content related to mental health generated more expressions of love and gratitude, whereas posts with content unrelated to mental health were more strongly associated with neutral or empathy/comprehension responses. This last connection is surprising, as it would be expected that posts that are coherent in terms of message content and accompanying image/video would generate more empathy or understanding, however, more factors come into play. Studies have found that the alignment between image and text can lead to higher engagement, but also, high-quality photographs or images, professionally taken are more highly valued (Li & Xie, 2020). Perhaps identifying with negative images is more difficult than with more pleasant images or videos, while dark images or those with crying or sad faces do not seem to generate more empathy, but rather more supportive reactions. It would be interesting to explore this further, as it is valuable information for designing more effective mental health awareness and promotion campaigns for SNs.

Lastly, posts with marketing purposes were clearly related to anger/mocking responses. This highlights the importance of how to reveal mental health issues or share this content on social media. Merely discussing mental health issues is not enough to promote positive emotions and create a more inclusive and tolerant society; the way messages are delivered, and their intended purpose are equally crucial.

Gronholm & Thornicroft (2022) already noted that both the message conveyed and the audience receiving it are fundamental for accepting mental health and truly generating a positive impact on the society. Our results support these findings; commodifying mental health and using it for commercial purposes generates anger and mocking, while sharing sincere messages accompanied by coherent content generally generates responses of love and gratitude. In the middle are messages that, although they talk about mental health, their overall content is not related to it, which seem to generate more neutral responses, although they also evoke understanding and empathy. Therefore, they can also be effective in promoting a positive view of mental health in the population, albeit to a lesser extent.

This study presents some limitations that should be considered when interpreting the results. First, the sample is limited to posts made by Spanish female influencers, which could skew the results towards a specific representation of gender and culture. The gender in the message is key to the social response it provokes. Intersectional stigma takes this phenomenon into account (the interaction of two types of stigmas, for example, towards mental health and towards women due to machismo, or conversely, stigma towards mental health and the traditional view of men as strong and <<not allowed to cry>>). In the case of this study, we decided to focus solely on responses to messages from women for this very reason. After reviewing the mental health posts that met the inclusion criteria, we observed that most were made by women. Specifically, only two or three posts made by men were identified, whose profiles differed significantly, as they were not influencers or content creators, but singers and actors. Therefore, given that the target audiences of both groups presented certain differences, we decided to analyze the posts by women and men separately and to limit this study exclusively to women. In future research, we plan to compare the responses generated by posts by women and men to delve deeper into the issue of gender and examine its influence on mental health and social perceptions.

Second, the research focused exclusively on Instagram, so the findings may not be generalizable to other social media platforms. Including other media such as TikTok or Twitter could provide a broader view of emotional responses. On the other hand, this research has not considered how Instagram's algorithm conditions the content that reaches the public or is promoted more. In our case, we accessed open posts using the inclusion criteria mentioned above. After reviewing the existing posts, we do not know if they generated more impact due to the platform's own algorithms. Nor did we have any way of controlling the responses posted by bots or automated comments. Similarly, we were unable to control whether the influencers moderated the comments they received in any way. As noted in the love/admiration comments, many positive responses were found, but they reflected little emotional connection to the post, which was not the case in comments classified as empathy.

Additionally, the analysis did not consider the emojis included in the posts, which means that many comments were not analysed. Furthermore, while literature reviews were conducted and different models of emotion classification were studied, sentiment analysis on social media finds notable challenges, including message brevity, lack of context, and frequent informal language. These obstacles are heightened in emotional analysis, where interpretation varies due to personal subjectivity, cultural differences in emotional expression, and individual variations in understanding emotions.

Finally, it is important to emphasize that the results should be interpreted with caution. This analysis is limited to female influencers whose main activity is content creation. It is possible that posts made by other profiles, aimed at different target audiences, may generate different responses. In this case, it would be necessary to retrain the artificial intelligence algorithm with a broader and more diverse corpus that takes these new cases into account. Looking ahead, we plan to continue researching in this area to assess whether the algorithm developed remains valid and capable of generalization in other contexts and types of posts.

5. Conclusions

This study offers valuable insights into the predominant emotions in responses to posts by Spanish influencers discussing mental health issues, utilizing innovative AI and NLP techniques. By integrating these advanced technologies, the research enhances the accuracy and depth of emotional analysis, paving the way for more effective understanding and engagement with mental health topics.

The results show that positive emotions such as love/admiration and comprehension/empathy are predominant in this type of content, suggesting that users tend to show support and acceptance when influencers share personal aspects related to their mental health. In contrast, negative emotions such as anger/mocking are less frequent but are primarily associated with promotional videos, suggesting that users may perceive this content as less authentic or motivated by commercial interests.

These findings have important implications for understanding the emotional dynamics generated on social media in response to mental health content, suggesting that visual elements and perceived authenticity play a key role in audience reactions. Furthermore, this study provides a novel approach by applying AI in the identification of emotions, which could be a useful tool in the future to evaluate social media intervention campaigns aimed at promoting mental health, as well as fostering more inclusive and respectful virtual contexts.

In fact, the integration of AI into mental health analysis represents a transformative innovation that is only beginning to be explored. This integration offers unprecedented opportunities in this context and should be accessible to researchers and professionals through online platforms that prioritize usability and data visualization. Thus, developing specialized software to facilitate the transfer of these technologies to business models could have a considerable impact. Therefore, it would be highly valuable to design intuitive software applications that not only support emerging business models but also provide real-time analysis and interactive visualizations, enabling professionals to make informed, strategic decisions.

As a conclusion, using ML and NLP models to interpret societal reactions to mental health messages offers a novel and impactful approach, especially given the importance of mental health awareness across societies today.

Ethics and Transparency

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Conflict of Interest

The authors declare no conflict of interest.

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Author Contributions

Contribution	Author 1	Author 2	Author 3	Author 4
Conceptualization	X	X	X	X
Data curation	X	X	X	X
Formal Analysis	X	X	X	X
Funding acquisition				
Investigation	X	X	X	X
Methodology	X	X		X
Project administration				X
Resources			X	
Software				X
Supervision	X	X	X	X
Validation	X	X	X	X
Visualization	X	X	X	X
Writing – original draft	X	X	X	X
Writing – review & editing	X	X	X	X

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

Adeane, E., & Stasiak, K. (2024). It's really hard to strike a balance: The role of digital influencers in shaping youth mental health. Digital Health, 10. https://doi.org/10.1177/20552076241288059

Al-Rawi, A. (2017). Viral news on social media. Digital Journalism, 7(1), 63–79. https://doi.org/10.1080/21670811.2017.1387062

Alhussein, G., Ziogas, I., Saleem, S., & Hadjileontiadis, L. J. (2025). Speech emotion recognition in conversations using artificial intelligence: A systematic review and meta-analysis. Artificial Intelligence Review, 58, 198. https://doi.org/10.1007/s10462-025-11197-8

Arcila Calderón, C., Van Atteveldt, W., & Trilling, D. (2021). Métodos computacionales y big data en la investigación en comunicación: Editorial dossier. Cuadernos.info, 49, I–IV. https://doi.org/10.7764/cdi.49.35333

Audrezet, A., De Kerviler, G., & Moulard, J. G. (2020). Authenticity under threat: When social media influencers need to go beyond self-presentation. Journal of Business Research, 117, 557–569. https://doi.org/10.1016/j.jbusres.2018.07.008

Baquerizo-Neira, M. G., Labate, C., Zerega Garaycoa, M. M., Cisternas Osorio, R., & Becker Cantariño, L. M. (2025). Identidad digital y comunicación de contenidos de influencers del bienestar emocional hispanoamericanos. Revista

Española de Comunicación en Salud, 16(1), 89–105. https://doi.org/10.20318/recs.2025.9315

Benton, M., Wittkowski, A., Edge, D., Reid, H. E., Quigley, T., Sheikh, Z., & Smith, D. M. (2024). Best practice recommendations for the integration of trauma-informed approaches in maternal mental health care within the context of perinatal trauma and loss: A systematic review of current guidance. Midwifery, 131, 103949. https://doi.org/10.1016/j.midw.2024.103949

Berger, J., & Milkman, K. L. (2012). What makes online content viral? Journal of Marketing Research, 49(2), 192–205. https://doi.org/10.1509/jmr.10.0353

Bernal-Delgado, E., Angulo-Pueyo, E., Ridao-López, M., Urbanos-Garrido, R. M., Oliva-Moreno, J., García-Abiétar, D., & Hernández-Quevedo, C. (2024). Spain: Health system review 2024. Health Systems in Transition, 26(3), 1–187. https://tinyurl.com/mpjwjm8j

Budenz, A., Klassen, A., Purtle, J., Yom Tov, E., Yudell, M., & Massey, P. (2020). Mental illness and bipolar disorder on Twitter: Implications for stigma and social support. Journal of Mental Health, 29(2), 191–199. https://doi.org/10.1080/09638237.2019.1677878

Cervantes Olivera, J. (2025). El impacto de las redes sociales en las emociones de los adolescentes de 12 a 18 años: Sentido de pertenencia. Ciencia y Reflexión, 4(2), 920–945. https://doi.org/10.70747/cr.v4i2.332

Chang, Y. P., Lin, Y. C., & Chen, L. H. (2012). Pay it forward: Gratitude in SNs. Journal of Happiness Studies, 13(5), 761–781. https://doi.org/10.1007/s10902-011-9289-z

Confederación Salud Mental España y Mutua Madrileña. (2023). La situación de la salud mental en España. https://tinyurl.com/y6zc7mkh

Connelly, L. (2019). Chi-square test. Medsurg Nursing, 28(2), 127. https://tinyurl.com/4efezw95

DataReportal. (2024). Digital 2024: Spain. DataReportal Global Digital Series. https://tinyurl.com/ycvdjch9

Ekman, P. (2003). Emotions revealed: Recognizing faces and feelings to improve communication and emotional life. Times Books.

Francis, D. B. (2021). Twitter is really therapeutic at times: Examination of Black men's Twitter conversations following hip-hop artist Kid Cudi's depression disclosure. Health Communication, 36(4), 448–456. https://doi.org/10.1080/10410236.2019.1700436

Franssen, G. (2019). The celebritization of self-care: The celebrity health narrative of Demi Lovato and the sickscape of mental illness. European Journal of Cultural Studies, 23(1), 89–111. https://doi.org/10.1177/1367549419861636

Fundación AXA. (2024). Estudio internacional de salud mental AXA España. https://tinyurl.com/3x5d5ncf

Gronholm, P. C., & Thornicroft, G. (2022). Impact of celebrity disclosure on mental health-related stigma. Epidemiology and Psychiatric Sciences, 31, e62. https://doi.org/10.1017/S2045796022000488

Ibáñez-Hernández, A., & Carretón-Ballester, C. (2025). La visibilidad de la epidemia en Instagram: El rol de los influencers como creadores de contenido en salud. Index.comunicación, 15(2), 83–108. https://doi.org/10.62008/ixc/15/02Lavisi

Lee, Y. H., Yuan, C. W., & Wohn, D. Y. (2021). How video streamers' mental health disclosures affect viewers' risk perceptions. Health Communication, 36(14), 1931–1941. https://doi.org/10.1080/10410236.2020.1808405

Li, Y., & Xie, Y. (2020). Is a picture worth a thousand words? An empirical study of image content and social media engagement. Journal of Marketing Research, 57(1), 1–19. https://doi.org/10.1177/0022243719881113

Lindgren, S. (2025). Digital media and society. Sage.

López-de-Ayala, M. C., & Díaz-Lucena, A. (2025). Instagram como plataforma para la salud mental: Evolución de las estrategias de publicación y compromiso. Miguel Hernández Communication Journal, 16(2), 467–484. https://doi.org/10.21134/tkb48j06

Luo, M., & Hancock, J. T. (2020). Self-disclosure and social media: Motivations, mechanisms and psychological well-being. Current Opinion in Psychology, 31, 110–115. https://doi.org/10.1016/j.copsyc.2019.08.019

Mardon, R., Cocker, H., & Daunt, K. (2023). When parasocial relationships turn sour: Social media influencers, eroded and exploitative intimacies, and anti-fan communities. Journal of Marketing Management, 39(11–12), 1132–1162. https://doi.org/10.1080/0267257X.2022.2149609

Marwick, A. E. (2015). Instafame: Luxury selfies in the attention economy. Public Culture, 27(75), 137–160. https://doi.org/10.1215/08992363-2798379

Merayo, N., Ayuso-Lanchares, A., & González-Sanguino, C. (2024). Machine learning and natural language processing to assess the emotional impact of influencers' mental health content on Instagram. PeerJ Computer Science, 10, e2251. https://doi.org/10.7717/peerj-cs.2251

Merayo, N., Ayuso-Lanchares, A., & González-Sanguino, C. (2025). Revealing emotional insights from mental health discussions on Instagram and TikTok using BERT models. IEEE Transactions on Affective Computing, 16(4), 3279–3290. https://doi.org/10.1109/TAFFC.2025.3568074

Nelson, A. (2019). Ups and downs: Social media advocacy of bipolar disorder on World Mental Health Day. Frontiers in Communication, 4. https://doi.org/10.3389/fcomm.2019.00024

Oscar, N., Fox, P. A., Croucher, R., Wernick, R., Keune, J., & Hooker, K. (2017). Machine learning, sentiment analysis, and tweets: An examination of Alzheimer's disease stigma on Twitter. The Journals of Gerontology: Series B, 72(5), 742–751. https://doi.org/10.1093/geronb/gbx014

Ouvrein, G. (2025). Followers, fans, friends, or haters? A typology of the online interactions and relationships between social media influencers and their audiences based on a social capital framework. New Media & Society, 27(10), 5659–5690. https://doi.org/10.1177/14614448241253770

Papacharissi, Z. (2014). Affective publics: Sentiment, technology, and politics. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199999736.001.0001

Pendleton, S. M. (2023). Exploring stigma and Black mental health on Twitter. Journal of Health Communication, 28(7), 425–435. https://doi.org/10.1080/10810730.2023.2218288

Pérez-Castaños, S., Antón-Merino, J., & García-Santamaría, S. (2023). Emociones, liderazgo y redes sociales. Propuesta para su medición en materiales de campaña electoral. Revista Española de Investigaciones Sociológicas, 184, 125–144. https://doi.org/10.5477/cis/reis.184.125

Pérez, J. M., Furman, D. A., Alonso Alemany, L., & Luque, F. L. (2022). RoBERTuito: A pre-trained language model for social media text in Spanish. En Proceedings of the Thirteenth Language Resources and Evaluation Conference (pp. 7235–7243). European Language Resources Association.

Sánchez Castillo, S., Armayones Ruiz, M., & Meléndez-Labrador, S. (2025). La información sobre salud en la esfera digital. Index.comunicación, 15(2), 13–32. https://doi.org/10.62008/ixc/15/02Lainfo

Sun, Y., Wu, Y., Fan, S., Dal Santo, T., Li, L., Jiang, X., Li, K., Wang, Y., Tasleem, A., Krishnan, A., He, C., Bonardi, O., Boruff, J. T., Rice, D. B., Markham, S., Levis, B., Azar, M., Thombs-Vite, I., Neupane, D., … Thombs, B. D. (2023). Comparison of mental health symptoms before and during the COVID-19 pandemic: Evidence from a systematic review and meta-analysis of 134 cohorts. BMJ, 380, e074224. https://doi.org/10.1136/bmj-2022-074224

Tudehope, L., Harris, N., Vorage, L., & Sofija, E. (2024). What methods are used to examine representation of mental ill-health on social media? A systematic review. BMC Psychology, 12(1), 105. https://doi.org/10.1186/s40359-024-01603-1

Valenzuela-García, N., Maldonado-Guzmán, D. J., García-Pérez, A., & Del-Real, C. (2023). Too lucky to be a victim? An exploratory study of online harassment and hate messages faced by social media influencers. European Journal on Criminal Policy and Research, 29(3), 397–421. **https://doi.org/10.1007/s10610-023-09542-0**

Van Dijk, T. A. (2016). Discourse and knowledge. Cambridge University Press.

Withers, M., Jahangir, T., Kubasova, K., & Ran, M.-S. (2021). Reducing stigma associated with mental health problems among university students in the Asia-Pacific: A video content analysis of student-driven proposals. International Journal of Social Psychiatry, 68(4), 827–835. **https://doi.org/10.1177/00207640211007511**

Zerega Garaycoa, M. M., Tutivén-Román, C., Cisternas-Osorio, E., Labate, C., & Becker Cantariño, L. M. (2024). Spanish-speaking wellness influencers in the era of care: Trends and topics in 2023. Vivat Academia, 157, 1–25. **https://doi.org/10.15178/va.2024.157.e1533**

Zhang, Z., Reavley, N., Armstrong, G., & Morgan, A. (2025). Public disclosures of mental health problems on social media and audiences' self-reported anti-stigma effects. Health Promotion International, 40(1). **https://doi.org/10.1093/heapro/daae204**

Zsila, Á., Orosz, G., McCutcheon, L. E., & Demetrovics, Z. (2021). Individual differences in the association between celebrity worship and subjective well-being: The moderating role of gender and age. Frontiers in Psychology, 12. **https://doi.org/10.3389/fpsyg.2021.651067**