



Pain and Misinformation on Social Media: Digital Representations, Amplification, and Social Validation in Health Communication (2021–2025)

Enrique Barros Beracaza¹; Francisco García García²; Estrella Martínez Rodrigo³

¹Doctoral candidate, University of Granada, Social Sciences, Audiovisual Communication and Journalism;

²Director of the Doctoral School, University of Design, Innovation and Technology; ³Associate Professor of Audiovisual Communication and Advertising.

KEYWORDS

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ABSTRACT

Background: Pain-related misinformation circulates on social media, yet little is known about how narrative forms, platform environments, and community signals relate to its presence and circulation. This study examines how pain is digitally represented on social media and how these representations are associated with misinformation, amplification, credibility markers, and the social validation of testimony. Methods: We analyzed 550 public pain-related posts (110 per platform; ≥ 50 comments) on Facebook, Instagram, TikTok, X, and YouTube (2021–2025), coding narrative form, credibility markers, social validation, and engagement. Multivariable logistic regression with robust variance estimated adjusted odds ratios (aORs), predicted probabilities, and ROC curves; a qualitative subsample (N=300) supported a thematic analysis. Results: Misinformation prevalence was 17.27% (95/550). Spectacle was associated with higher odds of misinformation (aOR 11.03; 95% CI 3.50–34.80) and Testimonial with lower odds (aOR 0.17; 0.04–0.75). Instagram had the highest adjusted probability (Pr=0.3945) and YouTube the lowest (Pr=0.0238). Amplification was positively associated with misinformation (aOR 1.79; 1.28–2.52), with median engagement of 35,159 versus 4,993 in posts without misinformation. In extended models, empathic social validation showed a protective gradient (V5 vs V1: aOR 0.0500; 0.0165–0.1515) and declared professional identity was associated with lower risk (aOR 0.36; 0.19–0.70). The model had an AUC of 0.884 (95% CI 0.806–0.905). Conclusions: Misinformation was linked to specific narrative frames, platform heterogeneity, and amplification, whereas professional identity and empathic validation were protective. These findings inform platform-specific mitigation, digital literacy, and message-design interventions focused on framing, traceability, and clinical safety.

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1. Introduction

In the contemporary communication ecosystem, social media have become central spaces for producing, circulating, and negotiating narratives about health and illness. In these environments, experiences historically confined to bodily privacy or clinical settings, such as pain, acquire unprecedented visibility through text posts, short videos, images, and hybrid formats mediated by algorithms. Platforms such as Facebook, Instagram, TikTok, YouTube, and X host a constant stream of personal accounts, educational content, therapeutic advice, and alternative discourses on pain,

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which coexist with institutional campaigns, health content creators, and commercial dynamics. This network creates an information environment characterized by rapid circulation, competition for attention, and the algorithmic amplification of particular narrative styles (Cinelli et al., 2020; Eysenbach, 2020; WHO, 2021; Allcott & Gentzkow, 2017; Lazer et al., 2018).

Research on health misinformation on social media has grown rapidly over the past decade, becoming an established field within health communication. A recent bibliometric analysis shows that scientific output is concentrated on topics with substantial media impact, such as vaccines, infectious diseases, and public health, and in regions with strong research infrastructure, particularly North America and Europe (Yeung et al., 2022). However, this development contrasts with the limited attention devoted to highly prevalent clinical conditions such as pain, whose presence in the digital ecosystem remains fragmented and insufficiently systematized. This imbalance reveals an important gap: despite its clinical and social centrality, pain remains understudied as a subject of misinformation in digital environments.

The digital ecosystem offers important opportunities to make suffering visible, provide peer support, and promote health literacy, but it also introduces well-documented risks associated with the infodemic, causal oversimplification, and the circulation of unverified information. False information tends to spread faster, farther, and more widely than verified information, driven by its novelty, emotional intensity, and capacity to generate surprise or outrage (Vosoughi et al., 2018; Pennycook & Rand, 2019). These patterns are reinforced by cognitive and social mechanisms such as confirmation seeking, narrative coherence, and the influence of like-minded communities, which facilitate the acceptance and persistence of inaccurate content (Lewandowsky et al., 2020). In health, these dynamics manifest in multiple forms of misinformation, ranging from misleading claims to misinterpretations of scientific evidence or unsupported therapeutic recommendations (Brennen et al., 2020).

Compared with other topics with substantial media impact, such as vaccines, COVID-19, or cancer, pain has received relatively little attention as a specific subject of communication, despite its high prevalence and central role in everyday clinical practice. Available studies have focused on particular virtual communities or specific diagnoses, describing social media as spaces for emotional support, exchanges of coping strategies, and identity construction among people with chronic pain (Merolli et al., 2015; Goudman et al., 2022). More recent research has explored individual platforms, such as TikTok or YouTube, identifying recurring narrative patterns, attempts to legitimize suffering, and the circulation of therapeutic recommendations of varying quality (Nunes et al., 2021; Yalamanchili & Basch, 2023). These contributions have provided an initial map of the phenomenon, but tend to focus on isolated platforms, specific clinical conditions, or selected dimensions of content, without systematically integrating representations of pain, the epistemic quality of information, and the dynamics of social validation of testimony.-

These dynamics are particularly relevant on visual and short-video platforms such as TikTok and Instagram, where recent studies have documented extensive circulation of health information of heterogeneous quality and the coexistence of evidence-based, mixed, and non-evidence-based content, particularly on topics related to wellness, pain, and mental health (Adler et al., 2024; Basch et al., 2022; Zheluk et al., 2022). In these environments, message credibility is constructed not only from sources or declared professional training, but also, and sometimes primarily, from engagement metrics, narrative styles, and emotional resonance (Lin et al., 2016; Sundar, 2008).

The importance of pain as a subject of communication is reinforced by its distinctive clinical and epistemological status. Unlike other nosological entities with objectively measurable diagnostic markers, pain is defined as a subjective, sensory, and emotional experience whose clinical legitimacy depends largely on the account of the person experiencing it (IASP, 2020; Raja et al., 2020). Contemporary definitions emphasize that pain cannot be understood independently of its context or the meanings attributed to it by the individual, placing patient testimony at the center of clinical assessment and the therapeutic process. This centrality of personal accounts makes pain

particularly sensitive to dynamics of credibility, recognition, and epistemic dispute, both in consultations and in the social sphere.

Clinical and psychosocial evidence now conceptualizes pain as a biopsychosocial experience emerging from interactions among biological, psychological, and social processes, moving beyond exclusively nociceptive approaches (Melzack & Wall, 1965; Turk & Okifuji, 2002). Narrative and relational approaches in medicine have further developed this communicative dimension, recognizing patients as the primary epistemic authorities on their own experiences and emphasizing listening, empathy, and the co-construction of illness narratives (Frank, 1995; Charon, 2006). However, this dependence on personal accounts introduces a structural vulnerability: when testimony is questioned, minimized, or delegitimized, pain can become an experience of epistemic injustice, with important clinical and psychosocial consequences (Blease et al., 2017).-

Transferring these clinical and narrative frameworks to the digital environment introduces sociotechnical mediations that substantially shape pain communication. Social media platforms do not operate as neutral information channels, but as spaces governed by algorithms that prioritize particular formats, emotional tones, and narrative styles according to their capacity to generate interaction (WHO, 2021). In this context, the visibility of pain is influenced by the demands of attention, speed, and algorithmic performance, which tend to favor highly emotional, simplified, or performative content, often at the expense of clinical context and explanatory nuance.

At the same time, social media function as spaces for the public validation of testimony. Through comments, reactions, and interaction metrics, audiences confirm, amplify, or question shared pain narratives, generating climates of support or invalidation that extend beyond individual posts. This social validation, predominantly empathic in pain communities, serves an important psychosocial function by counteracting previous experiences of disbelief or stigmatization (Merolli et al., 2015). However, emotional support does not necessarily distinguish between content of differing epistemic quality, meaning that clinically problematic messages may receive levels of recognition comparable to those afforded to rigorous information.

The convergence of high social validation and epistemic heterogeneity places pain in a particularly sensitive position within the digital ecosystem. Part of the negotiation over the legitimacy of pain and treatment expectations thus takes place outside healthcare settings, in opaque and highly dynamic algorithmic contexts, with direct implications for the clinical relationship and health communication (Topol, 2019).

Against this backdrop, a systematic analysis is needed to understand how digital representations of pain, the risk of misinformation, and the dynamics of social validation of testimony interact across platforms. The 2021–2025 period provides a particularly relevant analytical window, marked by the transition from the acute phase of the COVID-19 pandemic to a persistent infodemic, the consolidation of short audiovisual formats, and the growing professionalization and commercialization of health and wellness content creation. In this context, social media do more than disseminate information about symptoms, diagnoses, or treatments; they also organize forms of recognition, validation, dispute, and public amplification of suffering. Accordingly, this study aims to characterize digital representations of pain on social media and analyze their association with health misinformation, incorporating indicators of the social validation of testimony and markers of source credibility, through a comparative, multivariable analysis of posts on Facebook, Instagram, TikTok, X, and YouTube during 2021–2025.

2. Methods

2.1 Study design

We conducted an observational, cross-sectional analysis of digital content using a sequential explanatory mixed-methods approach (quantitative/qualitative). The unit of analysis was the individual post (post, video, reel, or thread) (Figure S1; Table S1). The quantitative component examined associations, without causal inference, between forms of pain representation and the presence of misinformation, adjusting for covariates of the communication environment (platform,

language, year), social engagement metrics, and markers of source credibility. The qualitative component involved a thematic analysis of a stratified, traceable subsample to contextualize the quantitative patterns through discursive devices and communication processes. Integration was achieved through narrative triangulation, comparing convergences and discrepancies between the two components. The cross-sectional design was considered appropriate for capturing patterns of representation and circulation in a dynamic digital ecosystem, without assuming temporal directionality or causal pathways.

2.2 Study setting, platforms, and time period

We analyzed public content from Facebook, Instagram, TikTok, YouTube, and X (formerly Twitter). Posts in Spanish and English published between January 1, 2021, and November 15, 2025, were included (Figure S1; Table S1, Panel A). Manual collection took place in 2024–2025, retrospectively capturing content within the defined time window using internal searches and default browsing settings on each platform (see 2.3). Threads was initially considered in an expanded scenario but was excluded from the main analysis because it did not meet the minimum interaction threshold (≥ 50 comments) required to estimate social validation, and therefore contributed no eligible posts (Table S1, Panel B).

2.3 Sampling and content search strategy

A target sample size of 110 posts per platform ($N=550$) was established for comparative purposes. Searches used queries based on hashtags and common clinical terms in the digital ecosystem (*#dolor*, “dolor crónico,” “migraña,” and “fibromialgia” in Spanish; *#pain*, chronic pain, migraine, and fibromyalgia in English), adapting the syntax and filters available in each application. Posts were assessed and selected in the default order of results provided by each platform at the time of capture, reflecting real-world user exposure dynamics. Sampling was nonprobabilistic. To mitigate biases arising from algorithmic ranking and virality, operational quotas and systematic selection were applied according to interface availability and documented by platform (Table S4, Panel B).

To limit dependence on a single source, an editorial rule of one post per account was applied; when an account produced multiple eligible results, the first post encountered in the search was selected. Duplicates and reposts were excluded both within and across platforms, avoiding repeated inclusion of identical or substantially equivalent content. The main reasons for exclusion by platform are summarized in Table S1 (Panel C).

2.4 Inclusion and exclusion criteria

Posts were included if they met the following criteria: (I) unrestricted public accessibility, (II) a publication date within the study period, (III) Spanish or English language, (IV) an explicit reference to pain in a health-related sense (a symptom, condition, or experience of pain), and (V) ≥ 50 comments at the time of capture (according to each platform’s default display). This threshold was established to ensure minimum density and comparability of the social validation indicator, calculated over a fixed comment observation window (the first 50 responses) (Table S2, Panel B).

We excluded profiles or content that were not publicly accessible; advertisements or purely commercial posts without substantive pain-related content; non-health-related metaphorical uses of the term “pain”; posts in languages other than Spanish or English; broken or unrecoverable links; duplicates and reposts (within and across platforms); posts outside the study period; and posts with < 50 comments. To avoid double counting, the main reasons for exclusion were operationalized as mutually exclusive categories (one reason assigned per candidate post) and are summarized overall and by platform in Table S1 (Panels A and C).

2.5 Data and metadata recording

Data were recorded using a standardized extraction template (see README/Supplementary Material). Each post was entered into a structured template and assigned a unique identifier

(record_id) to ensure traceability between components. The following were captured: platform, publication date/time (UTC), language, media type, text and/or audiovisual content transcript, publicly available interaction metrics (likes, comments, shares; views where available), hashtags, and contextual notes. Video content was transcribed manually, recording it as presented on the platform. Author identifiers were anonymized using alphanumeric codes, and direct identifiers were not retained in the analytical database. The eligibility of each field for the de-identified analytical dataset (including the exclusion of URLs/native IDs, text/transcripts, and raw hashtags because of tracing/re-identification risks) is detailed in Table S5. Operational definitions and decision rules for the recorded variables are presented in Table S3.

2.6 Operationalization of variables

Operationalization was based on a codebook developed and refined during a pilot phase following a review of the literature on pain, health communication, and digital misinformation. After the pilot, the codebook was standardized and applied consistently to the entire corpus, with prespecified decision rules for each variable. Operational definitions, levels/codes, and classification rules for the analytical variables are presented in Table S3 and the README. The operationalization of the social validation of testimony (empathic/invalidating/neutral classification, calculation of the social validation index [val_support_ratio], and construction of bands V1–V5) is detailed in Table S2. To facilitate reproducibility, analytical traceability and integrity checks (e.g., val_support_ratio $\in$ [0,1]) are documented in the reproducibility appendix (Table S6).

2.6.1 Forms of pain representation

Each post was classified into one dominant category: Testimonial, Clinical information, Spectacle, Meme, Activism/denunciation, or Naturopathic/complementary. Assignment followed a functional predominance rule, defined as the main frame organizing the message (communicative purpose and predominant narrative device), in accordance with the operational definitions and decision rules in the codebook (Table S3; README). For posts containing mixed elements, priority was given to the category that best reflected the content's central intent and organizing component (e.g., if the narrative revolved around an alternative therapeutic recommendation, it was classified as Naturopathic/complementary even if it included testimonial elements). For the quantitative analysis, this variable was operationalized as rep_form_id3 (see Tables S3 and S5). Coding discrepancies were resolved through double review and consensus, with adjudication documented (see 2.7).

2.6.2 Health misinformation

Misinformation was coded dichotomously (yes/no) as the presence of at least one verifiable health claim about pain, diagnosis, or treatment that was inaccurate, unsupported, or potentially misleading, in accordance with the information disorder framework and predefined operational criteria (Wardle & Derakhshan, 2017). Content was classified as misinformation when it included: (i) clinical claims unsupported by or contrary to available evidence; (ii) false causal attributions or causal oversimplifications presented as certain; (iii) unsupported therapeutic promises (e.g., “cures” or “eliminates pain” as a guarantee); (iv) minimization or omission of risks/adverse effects; (v) potentially dangerous recommendations, including explicit or implicit replacement of clinical care; and (vi) manipulation of sources (e.g., misrepresentation or an untraceable citation) when used to support a verifiable health claim. The absence of a source alone was not considered misinformation if no verifiable health claim was made; in such cases, it was recorded only as a credibility marker (Table S3). For the quantitative analysis, the outcome was operationalized as disinfo_bin (1=Yes; 0=No) (Tables S3 and S5). Decision rules and operational examples are detailed in the codebook and README in the supplementary material (Table S3).

2.6.3 Credibility markers

Next, the author's declared professional identity was recorded from credentials observable in the profile or content. Profession was initially captured in nominal categories (e.g., physician,

physiotherapist, pharmacist, massage therapist/osteopath, physical therapist, therapist/psychology, nutrition, other, none), without inferring credentials that were not explicit. For the multivariable analysis, it was operationalized as a binary variable (prof_bin: yes/no), used as an adjustment covariate in the models. Operational rules, harmonization criteria, and examples are detailed in the supplementary material/README.

Two credibility markers relating to the content and its source were coded. First, the presence of a cited source (source_cited_bin: yes/no) was defined as explicit inclusion of a verifiable, traceable reference supporting at least one health claim, including citation of a scientific article or technical document (title/author/year and/or link), a clinical guideline, consensus statement, or formal recommendation, and/or mention of a health institution accompanied by an identifiable document (e.g., organization + title/year/link). Generic institutional mentions without a retrievable reference were not considered a “cited source.” Source type (source_type) was also recorded for all posts, including the category “None” when no verifiable reference was identified. Because some categories had very low counts and cells with no events (complete separation), source type was reported mainly descriptively/bivariately using an analytical consolidation (source_type3) and an exact test (Table S10). To ensure stability in multivariable models, an alternative specification using a binary indicator of any source being present (source_any: source present vs none) was also evaluated as a robustness analysis (Table S11). Next, the author’s declared professional identity was recorded from credentials observable in the profile or content. Profession was initially captured in nominal categories (e.g., physician, physiotherapist, pharmacist, massage therapist/osteopath, physical therapist, therapist/psychology, nutrition, other, none), without inferring credentials that were not explicit. For the multivariable analysis, it was operationalized as a binary variable (prof_bin: yes/no) and used as an adjustment covariate in the models. Operational rules, harmonization criteria, and examples are detailed in the README. End of form. Beginning of form. Beginning of form.

2.6.4 Social validation of testimony

The climate of social validation was operationalized using val_support_ratio, calculated from the first 50 responses visible by default on each platform at the time of capture, to ensure a fixed, comparable window across platforms and avoid instability due to low interaction density. Each comment was classified as empathic/validating (E) or invalidating (I) according to prespecified codebook rules; neutral/unclassifiable comments were excluded from both the numerator and denominator (Table S2, Panel A). The continuous social validation index was defined as: $\text{val_support_ratio} = E / (E + I)$

When $(E + I) = 0$, the index was recorded as not calculable (missing) (Table S2, Panel B). For descriptive purposes and extended analyses, the continuous social validation index (val_support_ratio) was discretized into five ordinal bands defined a priori: V5 ≥ 0.90 ; V4 0.75–0.89; V3 0.60–0.74; V2 0.45–0.59; V1 < 0.45 (val_support_band_id; Table S2, Panel B). Because comments are observed after publication, this indicator was interpreted as a concomitant signal of social reception and used exclusively in extended models and sensitivity analyses (Tables S7–S9). The integrity of the index (bounded within [0,1]) and reproducible checks are documented in the README.

2.6.5 Engagement

Engagement was operationalized as a composite index of public interaction: $\text{engagement_raw} = n_likes + n_comments + n_shares$, recording the metrics visible at capture according to availability on each platform. Views (n_views) were not included in the index because of heterogeneity in their definition, availability, and comparability across platforms. To reduce skewness and approximate normality, a logarithmic transformation was applied: $\text{engagement_log} = \ln(\text{engagement_raw} + 1)$. The indicator was then standardized for analytical use (engagement_log_z , continuous). Because platforms differ in the scale and visibility of their interaction metrics, this standardization allowed engagement to be expressed as a relatively comparable measure across the analytical set. Operational definitions and the exact variable names used in Stata are detailed in the supplementary material/README.

2.6.6 Dominant clinical topic

A dominant clinical topic was identified from hashtags and the main clinical content of each post. Four categories were used: general pain ($\#Dolor/\#pain$), chronic pain ($\#Dolorcrónico/\text{"chronic pain"}$), fibromyalgia ($\#Fibromialgia/\#fibromyalgia$), and migraine ($\#Migraña/\#migraine$). When explicit clinical hashtags were present, the topic was assigned according to the first clinical hashtag identified in the post and operationalized in the analytical set as hashtags_paper_id (reference category: $\#Dolor$). In posts without explicit clinical hashtags, the topic was determined from the text and/or audiovisual transcript using prespecified codebook rules. The operational definition, decision rules, and final levels of the variable are described in Table S3 (final codebook) and the README/Supplementary Material.

2.7 Coder training and reliability

Two coders underwent one week of intensive training, reviewing relevant literature and actual platform posts. An initial pilot ($\approx 10\%$ of the corpus; $n \approx 55$) was conducted to refine criteria and adjust the codebook; after this phase, the instrument was standardized and applied consistently to the entire corpus. All posts (100%) were coded independently. Inter-rater agreement, estimated using Cohen's κ , was $\kappa = 0.708$ for forms of representation and $\kappa = 0.861$ for misinformation. Discrepancies (111/550; 20.18%) were resolved by consensus, with decisions documented in adjudication fields. In the qualitative subsample, 100% of posts were double-coded to ensure consistency, and discrepancies were resolved by consensus. Final rules, operational examples, and adjudication traceability are detailed in Table S3 and the README.

2.8 Quantitative analysis

Analysis was performed in Stata v19.5. Descriptive statistics were estimated overall and stratified by platform, form of representation, language, year, and clinical topic. Bivariate comparisons used χ^2 tests or Fisher's exact test when expected frequencies were low or cells were sparse. Continuous variables were summarized using the median and interquartile range (IQR). The main multivariable analysis used logistic regression (model M2; outcome: misinformation [yes/no]), reporting adjusted odds ratios (aORs), 95% CIs, and robust standard errors. The model included form of representation (rep_form_id3 ; ref.: Clinical information), platform (platform_id ; ref.: Facebook), language (language_id ; ref.: Spanish), year as a categorical variable (ref.: 2021), standardized engagement (engagement_log_z , continuous), a verifiable cited source (source_cited_bin ; ref.: No), declared professional identity (prof_bin ; ref.: No), and thematic hashtag (hashtags_paper_id ; ref.: $\#Dolor$). Completeness of the analytical set was verified, with no missing values in model covariates. Adjusted predicted probabilities (margins) by platform and form of representation (Figures 1–2) were estimated using margins. The main model's discriminatory ability was assessed using the ROC curve and area under the curve (AUC) (Figure 3).

For sensitivity/robustness analyses (supplementary material), extended models were estimated incorporating social validation as a continuous covariate (val_support_ratio ; Table S7) and as ordinal bands V1–V5 ($\text{val_support_band_id}$; Table S8), including adjusted margins by band (Table S9). In addition, given low frequencies and complete separation in some source-type

categories, source type was reported descriptively with an exact test (source_type3; Table S10), and a stable alternative model was estimated by replacing source_cited_bin with a binary indicator of source presence (source_any; Table S11).

2.9 Qualitative component and integration

A stratified subsample of N=300 (60 per platform), linked to the quantitative component through record_id, was analyzed qualitatively. The subsample was selected using stratified purposive sampling to ensure comparability across platforms and capture variation in forms of representation and the presence/absence of misinformation. The qualitative analysis was hybrid (inductive–deductive) and was conducted without specialized software through analytical reading, standardized analytical memos, and systematic recording of paraphrased evidence. For each post, a primary theme, optional subtheme, paraphrased evidence, and analytical memo were recorded. Quantitative–qualitative integration used narrative triangulation, comparing convergences and discrepancies between quantitative patterns and emerging themes.

The primary qualitative theme was not considered equivalent to the form of representation used in the quantitative model: the latter classified the dominant communicative frame of the post, whereas the primary theme identified the central thematic content emerging in the analyzed subsample.

2.10 Ethical considerations

Only unrestricted publicly accessible content was used, without interacting with users or collecting personally identifiable data. Author identifiers were anonymized, and qualitative evidence was presented through paraphrases to minimize the risk of re-identification. Given the observational nature of the study of public sources, ethics committee review was not required under applicable regulations; nevertheless, the project followed principles of respect, protection, and risk minimization, in accordance with ethical recommendations for research in digital environments (AoIR, 2019) and international ethical principles for research involving human participants and data (World Medical Association, 2024). The procedure complied with each platform's terms of service.

3. Results

3.1 Selection flow and exclusions

Across the five included platforms (Facebook, Instagram, TikTok, X, and YouTube), 8,479 candidate posts from 2021–2025 were assessed; 7,929 were excluded for one main reason each, and 550 posts (110 per platform) were included in the quantitative analysis. The main reasons for exclusion were: <50 comments (n=5,679), a language other than Spanish or English (n=384), no clinical pain expressed (n=242), duplicate (n=472), outside the study period (n=442), and repost (n=710) (Table S1). In the expanded scenario incorporating the excluded platform Threads, 11,581 candidates were assessed; 11,031 were excluded for one main reason each, and 550 remained included (Threads: 0 included). On Threads, the main reasons for exclusion were: <50 comments (n=2,431), a language other than Spanish or English (n=105), no clinical pain expressed (n=101), duplicate (n=178), and repost (n=287) (Table S1).

3.2 Characteristics of the analytical sample

The final sample included 550 posts, with a balanced distribution by platform (110 per platform; 20.0%). Misinformation prevalence was 95/550 (17.27%). The predominant forms of representation were Clinical information (268/550; 48.73%), Naturopathic/complementary (119/550; 21.64%), and Testimonial (93/550; 16.91%). Spanish was the predominant language (471/550; 85.64%). The temporal distribution was concentrated in 2025 (278/550; 50.55%) and 2024 (130/550; 23.64%). Regarding credibility markers, a cited source was present in

60/550 (10.91%), and declared professional identity in 279/550 (50.73%). Media types were Video 397/550 (72.18%), Text 83/550 (15.09%), and Image 70/550 (12.73%). Complete values are presented in Table 1.

3.3 Prevalence and distribution of misinformation

Overall misinformation prevalence was 17.27% (95/550). By platform, prevalence was highest on Instagram (40/110; 36.36%), followed by TikTok (25/110; 22.73%), Facebook (18/110; 16.36%), X (9/110; 8.18%), and YouTube (3/110; 2.73%). By language, it was higher in Spanish-language posts (90/471; 19.11%) than in English-language posts (5/79; 6.33%). By year, values were 31.58% in 2021, 12.50% in 2022, 10.94% in 2023, 18.46% in 2024, and 16.91% in 2025 (Table 1).

Among posts containing misinformation (n=95), the most frequent forms of representation were Naturopathic/complementary (30/95; 31.58%), Clinical information (37/95; 38.95%), and Spectacle (18/95; 18.95%); Testimonial accounted for 3/95 (3.16%). By platform, Instagram accounted for 40/95 misinformation cases (42.11%), TikTok 25/95 (26.32%), Facebook 18/95 (18.95%), X 9/95 (9.47%), and YouTube 3/95 (3.16%).

Posts containing misinformation had higher median engagement_raw than posts without misinformation: 35,159 (P25 6,033; P75 89,360) versus 4,993 (P25 1,401; P75 18,700). The val_support_ratio was lower in posts containing misinformation, with a median of 0.844 (P25 0.640; P75 0.978), compared with 1.000 (P25 0.940; P75 1.000) in posts without misinformation. The distribution across social validation bands also differed between groups, with higher proportions of misinformation in V1, V2, and V3 and a lower proportion in V5 (Table 1).

Explicit source citation was less frequent in posts containing misinformation (2/95; 2.11%) than in posts without misinformation (58/455; 12.75%). Declared professional identity was also less frequent in posts containing misinformation (33/95; 34.74%) than in posts without misinformation (246/455; 54.07%). Complete values and bivariate tests are presented in Table 1.

3.4 Associations in the main multivariable model

In the main multivariable logistic model M2 (N=550; robust variance estimation), form of representation was associated with misinformation relative to Clinical information: Spectacle had an aOR of 11.03 (95% CI 3.50–34.80; p<0.001), Naturopathic/complementary an aOR of 2.48 (95% CI 1.27–4.83; p=0.008), and Testimonial an aOR of 0.17 (95% CI 0.04–0.75; p=0.020). By platform, with Facebook as the reference, Instagram showed an aOR of 7.62 (95% CI 3.15–18.44; p<0.001), whereas YouTube had an aOR of 0.09 (95% CI 0.01–0.60; p=0.013). Engagement_log_z was positively associated with misinformation (aOR=1.79; 95% CI 1.28–2.52; p=0.001), whereas declared professional identity was inversely associated (aOR=0.36; 95% CI 0.19–0.70; p=0.003). Lower aORs were observed in 2023, 2024, and 2025 compared with 2021. Among hashtags, #Fibromialgia showed an aOR of 0.35 (95% CI 0.13–0.91; p=0.030). Complete results are presented in Table 2.

The main model's discriminatory ability was assessed using an ROC curve. The area under the curve was AUC=0.884 (95% CI 0.806–0.905), as shown in Figure 3.

3.5 Adjusted probabilities and thematic analysis

Adjusted probabilities of misinformation derived from model M2 differed across platforms and forms of representation. By platform, Instagram had the highest adjusted probability (Pr=0.3945; 95% CI 0.3030–0.4859), followed by TikTok (Pr=0.2179; 95% CI 0.1476–0.2882), Facebook

(Pr=0.1387; 95% CI 0.0796–0.1978), X (Pr=0.1019; 95% CI 0.0377–0.1661), and YouTube (Pr=0.0238; 95% CI –0.0080–0.0555) (Figure 1).

By form of representation, adjusted probability was highest for Spectacle (Pr=0.4543; 95% CI 0.2907–0.6180), followed by Naturopathic/complementary (Pr=0.2360; 95% CI 0.1770–0.2950), Activism/denunciation (Pr=0.2128; 95% CI 0.0052–0.4204), Meme (Pr=0.1785; 95% CI 0.0606–0.2964), Clinical information (Pr=0.1402; 95% CI 0.1015–0.1789), and Testimonial (Pr=0.0401; 95% CI –0.0034–0.0836) (Figure 2).

3.6 Sensitivity and robustness analyses

In the traceable qualitative subsample (N=300; 60 posts per platform), the most frequent primary theme was Clinical education and pain self-management (205/300; 68.33%), followed by Complementary therapies and therapeutic promises (39/300; 13.00%) and Testimony, identity, and legitimization of pain (32/300; 10.67%). The remaining themes were less frequent: Activism, denunciation, and epistemic dispute (10/300; 3.33%), Humor/trivialization and coping (8/300; 2.67%), and Spectacularization/performance of pain (6/300; 2.00%).

The distribution of misinformation varied by primary theme. The highest proportion was observed in Spectacularization/performance of pain (2/6; 33.33%), followed by Clinical education and pain self-management (47/205; 22.93%) and Humor/trivialization and coping (1/8; 12.50%). The bivariate association between primary theme and misinformation was significant ($\chi^2(5)=12.8601$; $p=0.025$). Complete values are presented in Table 3.

TABLE 1. Characteristics of the overall corpus and stratification by misinformation (N=550)

Variable	disinfo=0 (n=455)	disinfo=1 (n=95)	Total (N=550)
Misinformation, n (%)	455 (82.73)	95 (17.27)	550 (100.00)
Form of representation, n (%)			
Activism/denunciation	15 (3.30)	2 (2.11)	17 (3.09)
Spectacle	13 (2.86)	18 (18.95)	31 (5.64)
Clinical information	231 (50.77)	37 (38.95)	268 (48.73)
Naturopathic/complementary	89 (19.56)	30 (31.58)	119 (21.64)
Meme	17 (3.74)	5 (5.26)	22 (4.00)
Testimonial	90 (19.78)	3 (3.16)	93 (16.91)
Platform, n (%)			
Facebook	92 (20.22)	18 (18.95)	110 (20.00)
Instagram	70 (15.38)	40 (42.11)	110 (20.00)
TikTok	85 (18.68)	25 (26.32)	110 (20.00)
X	101 (22.20)	9 (9.47)	110 (20.00)
YouTube	107 (23.52)	3 (3.16)	110 (20.00)
Language, n (%)			
Spanish	381 (83.74)	90 (94.74)	471 (85.64)
English	74 (16.26)	5 (5.26)	79 (14.36)
Year, n (%)			
2021	26 (5.71)	12 (12.63)	38 (6.91)
2022	35 (7.69)	5 (5.26)	40 (7.27)
2023	57 (12.53)	7 (7.37)	64 (11.64)
2024	106 (23.30)	24 (25.26)	130 (23.64)
2025	231 (50.77)	47 (49.47)	278 (50.55)
Cited source, n (%)			
No	397 (87.25)	93 (97.89)	490 (89.09)
Yes	58 (12.75)	2 (2.11)	60 (10.91)
Declared professional identity, n (%)			
No	209 (45.93)	62 (65.26)	271 (49.27)
Yes	246 (54.07)	33 (34.74)	279 (50.73)

Variable	disinfo=0 (n=455)	disinfo=1 (n=95)	Total (N=550)
Media type (3 levels), n (%)			
Image	64 (14.07)	6 (6.32)	70 (12.73)
Text	74 (16.26)	9 (9.47)	83 (15.09)
Video	317 (69.67)	80 (84.21)	397 (72.18)
Emotional tone, n (%)			
pain/distress	75 (16.48)	13 (13.68)	88 (16.00)
hope/coping	20 (4.40)	12 (12.63)	32 (5.82)
humor/trivialization	5 (1.10)	2 (2.11)	7 (1.27)
indignation/denunciation	2 (0.44)	0 (0.00)	2 (0.36)
neutral/informative	353 (77.58)	68 (71.58)	421 (76.55)
Social validation band (V1–V5), n (%)			
V1	7 (1.54)	10 (10.53)	17 (3.09)
V2	7 (1.54)	6 (6.32)	13 (2.36)
V3	16 (3.52)	20 (21.05)	36 (6.55)
V4	52 (11.43)	24 (25.26)	76 (13.82)
V5	373 (81.98)	35 (36.84)	408 (74.18)
Thematic hashtag (topic), n (%)			
#Dolor	178 (39.12)	52 (54.74)	230 (41.82)
#Dolorcrónico	67 (14.73)	7 (7.37)	74 (13.45)
#Fibromialgia	106 (23.30)	13 (13.68)	119 (21.64)
#Migraña	104 (22.86)	23 (24.21)	127 (23.09)
engagement_raw, median (P25–P75)	4,993 (1,401-18,700)	35,159 (6,033-89,360)	6,078.5 (1,591-26,027)
engagement_log, median (P25–P75)	8.516 (7.246-9.836)	10.468 (8.705-11.400)	8.713 (7.373-10.167)
val_support_ratio, median (P25–P75)	1.000 (0.940-1.000)	0.844 (0.640-0.978)	1.000 (0.900-1.000)
EI, median (P25–P75)	50 (48-50)	49 (44-50)	50 (47-50)

Note. Categorical variables are reported as n (%). Continuous variables are reported as median (P25–P75).

TABLE 2. Main multivariable model (M2) for misinformation (N=550)

Covariate	aOR (95% CI)	P
Form of representation (ref.: Clinical information)		
Activism/denunciation	2.05 (0.30-14.13)	0.468
Spectacle	11.03 (3.50-34.80)	<0.001
Naturopathic/complementary	2.48 (1.27-4.83)	0.008
Meme	1.50 (0.44-5.12)	0.522
Testimonial	0.17 (0.04-0.75)	0.020
Platform (ref.: Facebook)		
Instagram	7.62 (3.15-18.44)	<0.001
TikTok	2.17 (0.92-5.13)	0.077
X	0.62 (0.19-2.08)	0.440
YouTube	0.09 (0.01-0.60)	0.013
Language (ref.: Spanish)		
English	1.27 (0.32-5.02)	0.735
Year (ref.: 2021)		
2022	0.28 (0.05-1.42)	0.123
2023	0.13 (0.03-0.62)	0.011
2024	0.10 (0.03-0.40)	0.001
2025	0.06 (0.02-0.22)	<0.001
engagement_log_z (continuous)	1.79 (1.28-2.52)	0.001
Cited source (ref.: No)		
Yes	0.31 (0.08-1.13)	0.077
Professional identity (ref.: No)		
Yes	0.36 (0.19-0.70)	0.003
Thematic hashtag (ref.: #Dolor)		
#Dolorcrónico	0.38 (0.13-1.09)	0.073
#Fibromialgia	0.35 (0.13-0.91)	0.030
#Migraña	0.55 (0.26-1.15)	0.112

Note. Logistic regression with robust standard errors. Reference categories: Clinical information; Facebook; Spanish; 2021; #Dolor; and "No" for cited source and professional identity. AIC=366.19; BIC=456.70.

TABLE 3. Primary themes in the qualitative subsample (N=300) and distribution by misinformation and platform

Primary theme (subsample)	n (%)	disinfo=1, n (row %)	Facebook	Instagram	TikTok	X	YouTube
Clinical education and pain self-management	205 (68.33)	47 (22.93)	27	58	60	15	45
Complementary therapies and therapeutic promises	39 (13.00)	4 (10.26)	15	1	0	11	12
Testimony, identity, and legitimization of pain	32 (10.67)	1 (3.12)	10	0	0	20	2
Activism, denunciation, and epistemic dispute	10 (3.33)	0 (0.00)	0	0	0	10	0
Humor/trivialization and coping	8 (2.67)	1 (12.50)	4	0	0	3	1
Spectacularization/performance of pain	6 (2.00)	2 (33.33)	4	1	0	1	0
Total	300 (100.00)	55 (18.33)	60	60	60	60	60

Note. Traceable subsample (N=300; 60 per platform). The disinfo=1 column is reported as n and row % within each theme. The primary theme corresponds to the qualitative analysis of the subsample and is not equivalent to the quantitative variable “form of representation” used in model M2. Pearson’s $\chi^2(5)=12.8601$; $p=0.025$.

Figure 1. Adjusted probability of misinformation by platform (M2).

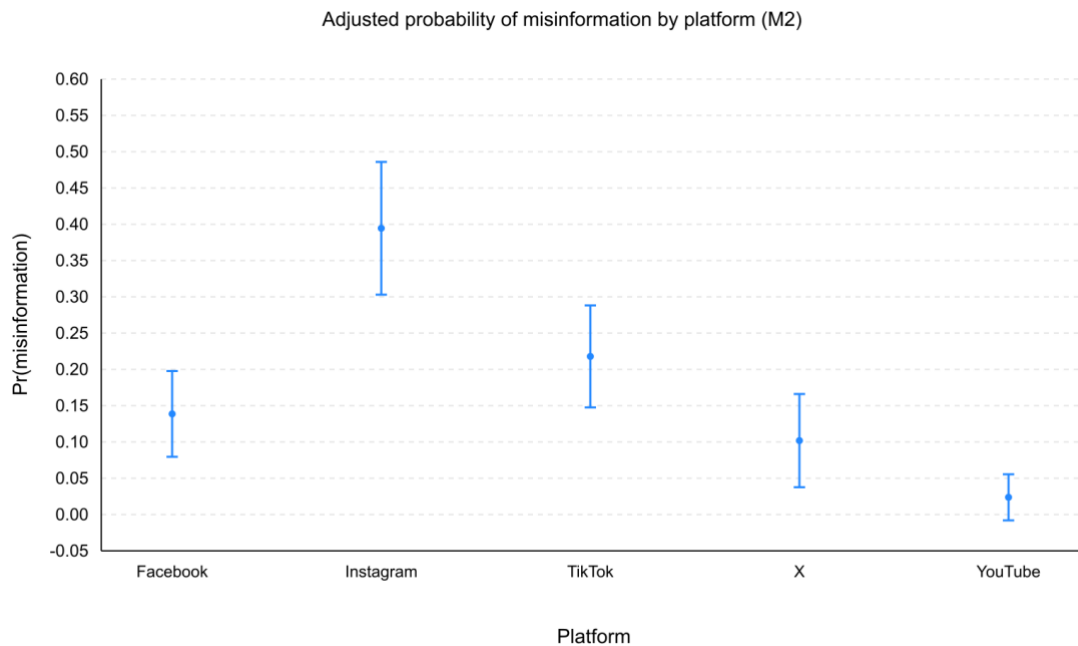


Figure caption. Adjusted probabilities of $\text{Pr}(\text{disinfo}=1)$ from model M2 (N=550): Facebook 0.1387 (95% CI 0.0796–0.1978); Instagram 0.3945 (0.3030–0.4859); TikTok 0.2179 (0.1476–0.2882); X 0.1019 (0.0377–0.1661); YouTube 0.0238 (–0.0080–0.0555).

Note: The 95% CIs were estimated using the delta method through margins (robust variance estimation). For predicted probabilities close to 0 or 1, CI limits may extend slightly beyond the theoretical range [0,1] because of the asymptotic approximation.

Figure 2. Adjusted probability of misinformation by form of representation (M2)

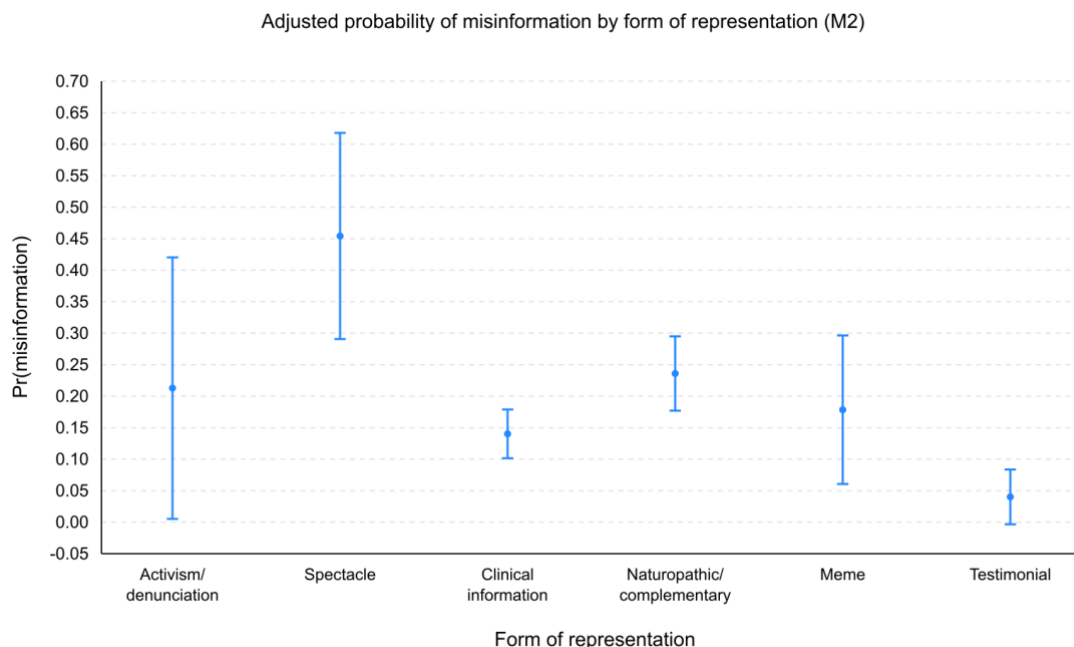
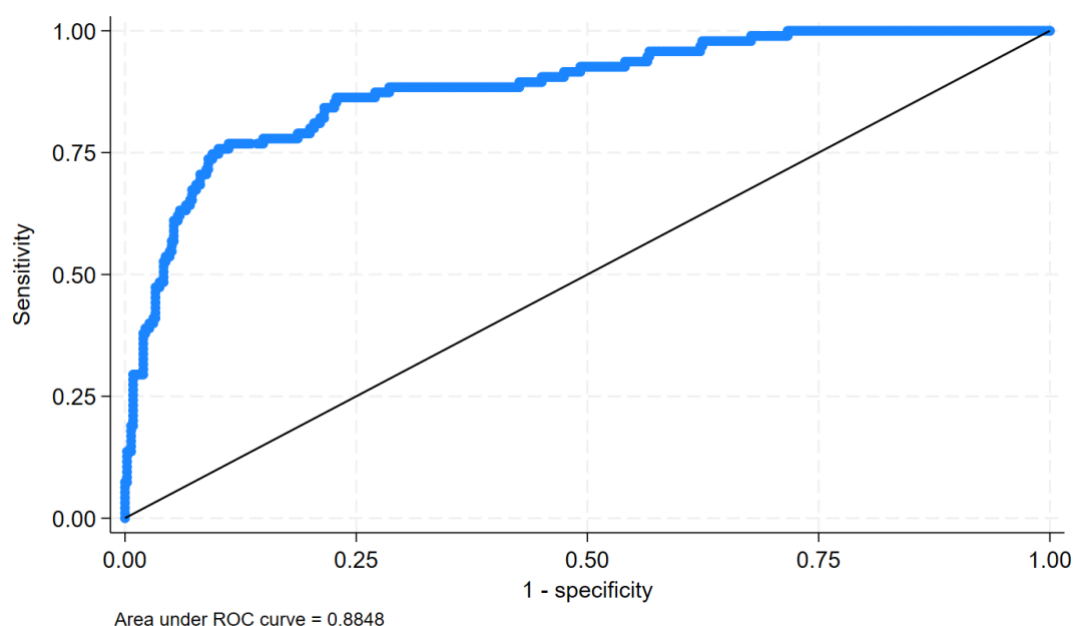


Figure caption. Adjusted probabilities of $\text{Pr}(\text{disinfo}=1)$ from model M2 (N=550): Activism/denunciation 0.2128 (95% CI 0.0052–0.4204); Spectacle 0.4543 (0.2907–0.6180); Clinical information 0.1402 (0.1015–0.1789); Naturopathic/complementary 0.2360 (0.1770–0.2950); Meme 0.1785 (0.0606–0.2964); Testimonial 0.0401 (–0.0034–0.0836).

Figure 3. ROC curve for the main model (M2).



Note. ROC curve for the multivariable logistic model classifying misinformation (*disinfo_bin*) in pain-related posts ($N=550$). The area under the curve was $AUC=0.884$ (95% CI 0.806–0.905), indicating high discriminatory ability. The diagonal line represents no discrimination ($AUC=0.5$).

4. Discussion

In this comparative multiplatform analysis (2021–2025), misinformation in digital pain-related content was not a trivial phenomenon: it was identified in 17.27% of posts (95/550) within a corpus balanced by platform (110 each) (Table 1). In the main multivariable model (M2), form of representation and platform were differentially associated with the probability of misinformation (Table 2), and the model showed high internal discrimination, $AUC=0.884$ (95% CI 0.806–0.905, Figure 3), suggesting that the combination of communication variables and the sociotechnical environment provides relevant signals for characterizing misinformation risk in this corpus. Taken together, these results support an interpretation consistent with contemporary information disorder and infodemic frameworks: rather than depending on an isolated “clinical topic,” misinformation may tend to cluster around communication processes (e.g., performance/spectacularization and therapeutic promises), conditions of visibility and circulation specific to the platform ecosystem, such as engagement, and source credibility signals, such as declared professional identity (Wardle & Derakhshan, 2017; World Health Organization [WHO], 2021).

4.1 Pain representations and differential misinformation risk

In the multivariable model (M2), the strongest association was observed for the Spectacle frame, with higher odds of misinformation relative to Clinical information ($aOR=11.03$; 95% CI 3.50–34.80). This pattern is consistent with the information disorder framework, in which certain performance-oriented narrative frames, often characterized by explanatory simplification, strong rhetorical certainty, and implicit promises, can function as effective communication vehicles for introducing or normalizing inaccurate or unsupported health claims (Wardle & Derakhshan, 2017). Similarly, Naturopathic/complementary showed a significant increase ($aOR=2.48$; 95% CI 1.27–4.83), consistent with the infodemic literature describing the circulation of wellness and

unconventional therapy messages featuring strong causal attributions, recommendations to replace care, and minimization of risks (WHO, 2021), and with the predominance of the theme “Complementary therapies and therapeutic promises” in the qualitative subsample (Table 3). In contrast, Testimonial was inversely associated with the outcome ($aOR=0.17$; 95% CI 0.04–0.75), suggesting that, under the operationalization used, narratives centered on lived experience and the legitimization of pain tend to contain fewer prescriptive or verifiable clinical claims that could be coded as misinformation. This finding should not be interpreted as equating “testimony” with biomedical accuracy, but as a difference in the density and type of statements (experiential vs prescriptive/assertive) that increase the probability of the outcome within this classification framework.

4.2 Platform effect: sociotechnical environment and governance of visibility

Platform heterogeneity was marked and consistent in the multivariable model. Compared with Facebook, Instagram showed higher odds of misinformation ($aOR=7.62$; 95% CI 3.15–18.44; $p<0.001$) and the highest adjusted probability (0.3945; 95% CI 0.3030–0.4859), whereas YouTube showed an inverse association ($aOR=0.09$; 95% CI 0.01–0.60; $p=0.013$) and a low adjusted probability (0.0238; 95% CI –0.0080–0.0555). Because the platform variable functions here as a proxy for a set of unobserved sociotechnical conditions, this gradient is compatible with the idea that platforms differ in their communication characteristics and visibility architectures (e.g., recommendation and discovery systems and interaction signals), as well as their governance and moderation practices for health content. Together, these may shape which narrative styles are amplified and become established in public conversation (Gillespie, 2018; Vosoughi et al., 2018; Cinelli et al., 2020). This interpretation is reinforced by the positive association between amplification (engagement) and misinformation after multivariable adjustment, suggesting that misinformation risk emerges at the intersection of platform environment and circulation dynamics. In practical terms, the findings support platform-specific, rather than uniform, mitigation strategies (message design, credibility signaling, and moderation actions).

4.3 Amplification and the attention economy: engagement as a condition of circulation

In the main multivariable model, greater amplification was independently associated with a higher probability of misinformation (engagement_log_z: $aOR=1.79$; 95% CI 1.28–2.52; $p=0.001$). Given the study’s observational design, this association cannot establish directionality or rule out reverse causality; however, it is consistent with previous evidence on diffusion dynamics in digital environments, where content generating greater social response tends to achieve higher visibility and, consequently, wider circulation (Vosoughi et al., 2018; Cinelli et al., 2020).

From a health communication perspective, this finding positions engagement as an important communicative condition for the circulation of inaccurate health claims. In the case of pain, this dynamic is particularly important because pain is a subjective, affective, and socially contested experience whose interpretation depends largely on personal accounts, the credibility attributed to the source, and audience responses. In this context, messages with high communicative salience—categorical formulations, promises of relief, performative accounts, polarization, or controversy—can stimulate public interaction without necessarily meeting criteria for clinical accuracy.

This result must be interpreted in light of a central methodological decision: the quantitative corpus was restricted to posts with ≥ 50 comments to ensure a sufficient, comparable basis for estimating the social validation of testimony. This restriction likely overrepresents content with high conversational interaction and underrepresents educational, institutional, or clinically rigorous messages that generate less participation. Consequently, the findings primarily describe the

segment of pain-related content with intense public conversation and greater exposure potential, rather than the entire universe of posts available on each platform.

This restriction does not invalidate the study's contribution, but clarifies its scope: the analysis focuses on the space in which misinformation is particularly relevant to public health communication, namely content that circulates, generates conversation, and attracts social attention. In practical terms, the results suggest that clinical communication and digital literacy strategies cannot be limited to producing accurate information; they must also compete in clarity, narrative relevance, and accessibility, without sacrificing traceability, caution, or clinical accuracy (Vraga & Bode, 2020; WHO, 2021).

4.4 Source credibility: protective signals and the limits of the “appearance of rigor”

Declared professional identity was consistently associated with a lower probability of misinformation in the multivariable model ($aOR=0.36$), suggesting that explicit credentials can operate as credibility heuristics in digital environments where judgments are made with limited information and substantial attentional demands (Metzger & Flanagin, 2013). At the same time, source citation showed a robust protective pattern at the descriptive/bivariate level (a lower proportion of misinformation when sources were cited), but the evidence was borderline after multivariable adjustment ($p=0.077$), consistent with its low frequency in the corpus and variability in reference traceability and quality when communication occurs in short or predominantly audiovisual formats.

This asymmetry is relevant to communication. On social media, certain superficial markers of “rigor,” such as generic references to “studies” or the inclusion of unrecoverable links, can function as rhetorical devices for legitimization without ensuring verifiability. Professional identity, although also imperfect and potentially unverifiable, may guide public interpretation and shape conversational norms (O'Connor & Weatherall, 2019). In a field such as pain, where subjectivity, expectations of relief, and therapeutic recommendations converge, improving information quality requires going beyond “citing”: it entails retrievable traceability (accessible, specific references), explicit acknowledgment of limitations and uncertainty, and clear communication of clinical safety considerations and decision criteria, reducing opportunities for unsupported prescriptive inferences (WHO, 2021).

4.5 Social validation and conversational climates: integration with the qualitative component

The extended analyses provide one of the study's most distinctive findings: empathic social validation was inversely associated with misinformation. This pattern was observed both when `val_support_ratio` was included as a continuous variable and when ordinal bands V1–V5 were analyzed, with higher bands showing lower adjusted probabilities of misinformation. Because comments occur after publication, this relationship must be interpreted as concomitant rather than directional. Nevertheless, the result positions social validation as a measurable communicative dimension that provides additional information about the environment in which content circulates, rather than as contextual “noise.”

Triangulation with the qualitative component reinforces this interpretation, although a methodological clarification is necessary. The primary qualitative theme and quantitative form of representation are not equivalent variables: the former describes the dominant thematic content, whereas the latter classifies the post's communicative frame. With this distinction in mind, the results suggest that thematically educational content may contain unsupported claims if it uses prescriptive devices, causal simplifications, or therapeutic promises. Conversely, testimony may contain less misinformation when it remains experiential and does not formulate verifiable clinical recommendations.

Taken together, these two layers—content and conversation—provide a useful basis for public communication about health. Strategies addressing misinformation should not be limited to correcting information, but should also consider conversational norms, forms of community validation, and discursive practices accompanying the public circulation of pain narratives.

4.6 Thematic microenvironments and temporal trends: observational signals

The thematic hashtag functioned as a proxy for discursive microenvironments and showed differentiated signals. In the multivariable model, #Fibromialgia was associated with a lower probability of misinformation than #Dolor, whereas #Dolorcrónico and #Migraña showed no conclusive evidence. This finding should be interpreted cautiously, because a hashtag is a self-reported marker rather than a clinical diagnosis. Rather than representing intrinsic properties of the topic, it may capture differences in communities, participation norms, source profiles, formats, and credibility repertoires.

A temporal signal of lower adjusted odds of misinformation in 2023–2025 compared with 2021 was also observed. However, given the cross-sectional design and nonprobability sampling, this pattern cannot be attributed to moderation policies, literacy campaigns, or specific transformations in the digital ecosystem. Its main value is exploratory: it suggests a hypothesis that should be evaluated through longitudinal designs, prospective sampling, and analyses capable of controlling for composition by platform, narrative frame, and amplification level.

4.7 Implications for clinical communication, digital literacy, and message design

The findings show that pain-related misinformation is not distributed uniformly, but is concentrated in particular narrative forms, platform environments, and amplification dynamics. Mitigation strategies should therefore prioritize contexts with the greatest communication risk, especially those where high visibility, performative formats, therapeutic promises, or low information traceability converge. In this sense, not all pain-related content requires the same intensity of response: monitoring, public correction, and message-design efforts should be sensitive to the platform, format, and dominant narrative type.

The inverse association observed for declared professional identity and the lower frequency of cited sources among posts containing misinformation suggest another practical implication: professional communication about pain must be visible, traceable, and adapted to platform-specific modes of expression. Producing accurate information is not enough; it must be communicated in brief, understandable, and competitive formats while retaining clinical caution, explicit acknowledgment of uncertainty, verifiable source retrieval, and safety signals about when to seek care or which practices to avoid.

Similarly, digital literacy about pain should focus not only on recommending “reliable sources,” but also on teaching people to recognize rhetorical risk signals: absolute guarantees of effectiveness, simplified causal explanations, promises of rapid relief, implicit replacement of clinical care, or minimization of risks. This approach is particularly important because pain combines high emotional intensity, diagnostic uncertainty, persistence over time, and frequent therapeutic frustration, conditions that may increase receptivity to messages promising certainty or immediate relief.

Finally, empathic social validation raises an additional implication. Responses to misinformation should not adopt an exclusively punitive or technocratic tone, because many digital pain communities provide real companionship and recognition. A more appropriate strategy should distinguish between validating a person’s suffering and validating unsupported clinical claims. This entails promoting nonconfrontational responses, respectful correction, cautious identification of risks, and community norms that offer support without amplifying potentially harmful recommendations.

Overall, the study points toward a digital health communication agenda based on three complementary levels: stratification by communication risk, a traceable professional presence, and digital literacy attentive to the rhetoric of promises, certainty, and replacement of clinical care. Rather than opposing evidence and experience, the results emphasize the need to formulate clinically cautious, communicatively competitive, and socially empathic messages in ecosystems where visibility, narrative form, and conversational climate shape which content acquires public legitimacy.

4.8 Strengths and limitations

The study has four notable strengths relevant to public communication about health. First, its comparative multiplatform approach, with a balanced corpus of 110 posts per platform, improves internal comparability across sociotechnical environments. Second, the 2021–2025 time window allows observation of digital ecosystem patterns following the acute phase of the COVID-19 infodemic, without relying on a single time point. Third, the multivariable analysis integrates communication predictors, form of representation, circulation conditions (engagement), and declared credibility signals—professional identity and source citation—with robust standard errors and adjusted probabilities. Fourth, triangulation with thematic analysis in a traceable subsample adds interpretive coherence by linking narrative repertoires and conversational climates to the outcome.

The limitations should be interpreted in a methodological hierarchy. First, nonprobability sampling limits generalization to the entire universe of pain-related posts. Second, restricting inclusion to posts with ≥ 50 comments, necessary to stabilize the social validation indicator, introduces a visibility bias toward highly interactive content; the results therefore primarily describe the most visible and conversational segment of the digital pain ecosystem. This restriction may underrepresent clinically rigorous, institutional, or scientific-society content that generates less engagement despite its information quality. Third, the observational, cross-sectional design precludes causal inference and cannot establish directionality between misinformation, amplification, and social validation. Fourth, the credibility signals included are declarative and may operate as communication heuristics without ensuring verifiability; moreover, the low frequency of “cited source” limits power and precision. Fifth, some combinations have sparse cells, restricting more disaggregated analyses. Finally, temporal associations should be read as observational signals potentially influenced by changes in corpus composition and platform-specific visibility dynamics, particularly in the period following the 2020–2021 infodemic.

Accordingly, the proposed practical implications should be understood as plausible guidance derived from consistent associations, rather than causally demonstrated effects of specific interventions.

4.9 Future research directions

Future studies should advance in four directions. First, replicate these findings using prospective sampling and/or longitudinal designs that more clearly distinguish initial exposure, amplification (engagement), and subsequent conversational dynamics, reducing the temporal overlap between posts and comments. Second, where methodologically and ethically feasible, incorporate reach/impression measures and algorithmic distribution metrics to approximate actual exposure beyond visible interaction. Third, evaluate message-design interventions that are clinically accurate yet competitive in the attention economy (e.g., short formats, safety-centered narratives, verifiable micromessages, uncertainty labels, and safe calls to action), ideally through experimental or quasi-experimental designs and platform-specific analyses. Fourth, investigate the communicative distinction between supporting the person and supporting the content: empathic validation can coexist with inaccuracies, making it useful to refine instruments that distinguish companionship,

respectful correction, risk identification, and verification, and to explore how these conversational functions vary across pain communities and contexts.

5. Conclusions

In a comparative multiplatform analysis of public pain-related posts (2021–2025; N=550), this study characterized digital representations of pain and assessed their association with health misinformation, incorporating social validation indicators and source credibility markers. Misinformation was observed in 17.27% of the corpus and varied by platform and narrative frame: in the multivariable model, Spectacle and Naturopathic/complementary frames were associated with a higher probability of misinformation than Clinical information, whereas Testimonial was associated with a lower probability. Comparisons across platforms revealed consistent differences in risk, and amplification (engagement) was positively associated with misinformation, positioning circulation as a central component of the phenomenon.

Regarding credibility, declared professional identity emerged as a protective signal, whereas source citation showed a less conclusive protective trend after multivariable adjustment, consistent with its low frequency and the limitations of traceability in short and audiovisual formats. The extended analyses consistently indicated a robust inverse association between empathic social validation and misinformation (val_support_ratio and the V1–V5 gradient), suggesting that conversational climate provides information beyond the post's content for characterizing misinformation risk. Overall, the findings support platform-specific mitigation and intervention strategies in pain communication, integrating clinically accurate message design that competes for attention, digital literacy focused on communication risk signals, and actions that jointly consider narrative frames, credibility, and social validation dynamics.

Conflicts of interest

The authors have no conflicts of interest to declare in relation to this article.

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Data availability

The data used in this study come from public posts available on social media. The analyzed corpus and variable dictionary may be obtained from the corresponding author upon request and in accordance with the platforms' usage policies.

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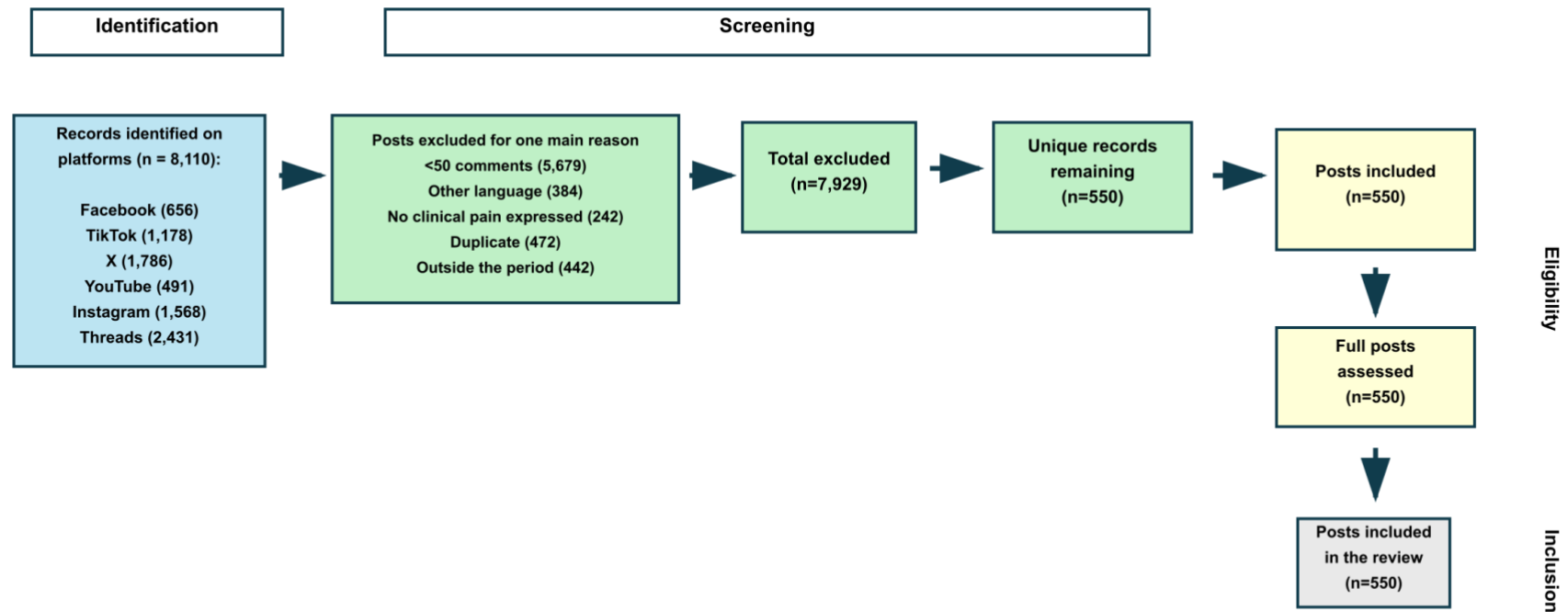
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7. Appendices

Figure S1. PRISMA flow diagram of corpus selection (2021–2025).



Note. A total of 8,479 candidates were assessed across five platforms; 7,929 were excluded for one main reason each, and 550 posts were included (110 per platform). The expanded scenario incorporating Threads is reported in Table S1 (Panel B).

Table S1. Selection flow and main reasons for exclusion by platform.

Panel A. Main scenario (five included platforms).

Stage / Main reason	n
Candidate posts assessed (2021–2025)	8,479
Excluded for one main reason (total)	7,929
• <50 comments	5,679
• Language other than Spanish or English	384
• No clinical pain expressed	242
• Duplicate	472
• Outside the study period	442
• Repost	710
Included posts (110 per platform)	550

Panel B. Expanded scenario incorporating Threads (Threads: 0 included).

Stage / Main reason (Threads)	n
Candidate posts assessed (Threads)	3,102
Excluded for one main reason (Threads)	3,102
• <50 comments	2,431
• Language other than Spanish or English	105
• No clinical pain expressed	101
• Duplicate	178

Stage / Main reason (Threads)	n
• Repost	287
Included posts (Threads)	0

Panel C. Main reason for exclusion by platform (including Threads).

Platform	<50 comments	Language ≠ ES/EN	No pain expressed	Duplicate	Outside the study period	Repost	Included	Total posts assessed
Facebook	656	81	27	110	96	198	110	1,278
TikTok	1,178	29	56	98	101	86	110	1,658
X	1,786	36	18	148	78	213	110	2,389
YouTube	491	159	68	27	38	61	110	954
Instagram	1,568	79	73	89	129	152	110	2,200
Threads	2,431	105	101	178	0	287	0	3,102

Note. Each excluded candidate was assigned one main reason (mutually exclusive). The <50-comment threshold was defined to ensure minimum density for calculating social validation.

Table S2. Social validation of testimony

Panel A. Coding rules

Category	Operational definition	Typical indicators	Examples (paraphrased)	Rules and borderline cases
Empathic (E)	Expresses recognition, legitimization, or support for the source's experience of pain.	Emotional validation, companionship, solidarity, recognition of suffering/limitations.	"I believe you / it is very hard"; "Thank you for sharing, you are not alone"; "Stay strong, I understand how you feel."	If support and doubt coexist, code according to the dominant emphasis. Questions without a stance → neutral.
Invalidating (I)	Minimizes, ridicules, discredits, or questions the legitimacy of the pain or account (including gaslighting).	Denial, blame, allegations of exaggeration, mockery, discrediting of testimony.	"It is not that bad"; "You are making it up/exaggerating"; "You could if you wanted to."	Classify sarcasm according to its effect (legitimizing vs ridiculing). If it cannot be interpreted confidently → neutral.
Neutral (N)	Neither validates nor invalidates pain; tangential or unassessable content.	Information-seeking questions without judgment, ambiguous emojis without context, spam, tags without content.	"What is your diagnosis?"; "What medication do you take?"; emojis without text.	Excluded from the calculation. If the comment contains an implicit judgment (e.g., blame), reclassify it as invalidating.

Panel B. Calculation of *val_support_ratio* and construction of ordinal bands (*val_support_band_id*).

Component	Definition / formula	Notes
Counts	E = number of empathic comments; I = number of invalidating comments (both within the first 50 responses).	Neutral comments are included in neither E nor I.
Main index	$\text{val_support_ratio} = E / (E + I)$ (range 0–1).	If $(E + I) = 0 \rightarrow$ not calculable (missing).
Ordinal variable	<i>val_support_band</i> (V1–V5) derived from <i>val_support_ratio</i> for ordinal analysis/description.	Predefined thresholds to avoid data-driven cutoffs.
Thresholds	V5 ≥ 0.90 ; V4 0.75–0.89; V3 0.60–0.74; V2 0.45–0.59; V1 < 0.45 .	Interpretation: from predominant invalidation (V1) to near-unanimous validation (V5).

Component	Definition / formula	Notes
Inclusion threshold	Only posts with ≥ 50 comments were included, so that the index could be based on a fixed number of responses.	Reduces instability in posts with low interaction.

Note. The first 50 responses visible in the default interface at capture were analyzed. Neutral comments were excluded from the numerator and denominator. If $(E+I)=0$, the index was recorded as missing.

Table S3. Final codebook (analytical variables and decision rules).

Variable	Operational definition	Type	Values / levels	Decision rules	Use
platform	Platform on which the content was published.	Categorical	Facebook; Instagram; TikTok; YouTube; X.	Code according to the post's origin.	Adjustment/stratum
date_utc	Publication date/time in UTC.	Date	Date time (UTC).	Standardize format; derive year.	Descriptive/adjustment
year	Publication year derived from date_utc.	Integer	2021-2025.	Derive from date_utc.	Adjustment/model
language	Predominant language of the content.	Categorical	Spanish; English.	Based on text/audio/subtitles.	Adjustment/stratum
media_type	Predominant media type.	Categorical	text; image; video; mixed.	Visual/functional predominance.	Descriptive
rep_form_primary	Dominant form of pain representation (predominant communicative function).	Categorical	clinical_info; testimony; spectacle; meme; activism; complementary alternative.	For hybrids, apply the functional predominance rule.	Main predictor
rep_form_secondary	Second relevant form (if applicable).	Categorical	Same levels as the primary form.	Record only if it adds substantive interpretation.	Exploratory
disinfo_present	Presence of health misinformation.	Binary	Yes/No (analytical).	"uncertain" for operational use only; exclude from the analytical set.	Main outcome
disinfo_type	Main misinformation type (if disinfo_present=Yes).	Categorical	unsupported_claim; miracle_cure; risk_minimization; stigmatizing_moral; source_manipulation.	Assign the dominant type; if multiple, prioritize the one posing the greatest clinical risk.	Descriptive/explanatory
source_cited	Cites at least one verifiable source/reference.	Binary	Yes/No.	Link, formal reference, or identifiable entity.	Covariate

Variable	Operational definition	Type	Values / levels	Decision rules	Use
source_type	Type of cited source (if source_cited=Yes).	Categorical	scientific; institutional; professional; anecdotal; link_no_context.	Classify according to the nature of the predominant reference.	Covariate
professional_identity_declared	The source declares a healthcare professional identity.	Binary	Yes/No.	Explicit self-declaration in the profile or content.	Covariate
Professional	Declared profession (if present and amenable to standardization).	Categorical	e.g., medicine, physiotherapy, psychology, nursing, etc.	Do not infer; record only if explicit.	Descriptive
safety_disclaimer_present	Safety/responsible-use warning.	Binary	Yes/No.	E.g., “consult a professional,” “not a substitute for medical care.”	Covariate
emotional_tone_primary	Predominant emotional tone of the content.	Categorical	dolor_angustia [pain/distress]; esperanza afrontamiento [hope/coping]; indignacion_denuncia [indignation/denunciation]; humor_banalizacion [humor/trivialization]; neutral_informativo [neutral/informative].	Integrate text, audio, and visuals; do not rely on an isolated comment.	Exploratory/int erpretive
n_views	Number of views (if available).	Integer	≥0.	Record at capture.	Descriptive
n_likes	Number of likes.	Integer	≥0.	Record at capture.	Engagement component
n_comments	Total number of comments.	Integer	≥0.	Threshold ≥50 for inclusion.	Criterion/inform ation

Variable	Operational definition	Type	Values / levels	Decision rules	Use
n_shares	Number of shares/reposts/retweets.	Integer	≥0.	Record at capture.	Engagement component
engagement_raw	Base index of social interaction.	Derived	n_likes + n_comments + n_shares.	Excludes views because of heterogeneity across platforms.	Intermediate
engagement_zcore	Z-score of engagement calculated within each platform.	Continuous	Mean 0; SD 1 (per platform).	engagement_zcore=(raw mean_platform)/sd_platform.	Predictor
val_empathy_comments_n	Number of empathic comments (first 50 responses).	Integer	0-50.	See S1.	Validation component
val_invalidation_comments_n	Number of invalidating comments (first 50 responses).	Integer	0-50.	See S1.	Validation component
val_support_ratio	Continuous social validation index.	Continuous	0–1; missing if E+I=0.	See S1.	Secondary outcome
val_support_band	Ordinal bands V1–V5 derived from val_support_ratio.	Ordinal	V1-V5.	See S1; predefined thresholds.	Secondary outcome
coder_id_primary	Primary coder identifier.	ID	Internal codes.	Does not identify individuals in public materials.	QA
coder_id_secondary	Second coder identifier (if double-coded).	ID	Internal codes.	Applicable to the reliability subsample.	QA
adjudicated_by	Adjudicator identifier.	ID	Internal codes.	Resolution of discrepancies through consensus/adjudication.	QA
adjudicated_date	Adjudication date.	Date	YYYY-MM-DD.	Record only if applicable.	QA
adjudicated_rep_form_primary	Final representation category after adjudication.	Categorical	Levels of rep_form_primary.	Use when coders disagree.	QA

Variable	Operational definition	Type	Values / levels	Decision rules	Use
adjudicated_disinfo_present	Final misinformation classification after adjudication.	Binary	Yes/No.	Use in case of discrepancy.	QA
adjudicated_disinfo_type	Final misinformation type after adjudication.	Categorical	Levels of disinfo_type.	Use in case of discrepancy.	QA
notes_free_text	Coder's internal contextual notes.	Text	Free text.	Not suitable for open publication because of tracing/re-identification risks.	Internal

Table S4. Search strategy and platform-specific adaptation (Panels A–B).

Block	Spanish (examples)	English (examples)	Notes
Pain (clinical/common usage)	dolor crónico; dolor agudo; dolor neuropático; lumbalgia/ciática; migraña/cefalea; fibromialgia; artritis/artrosis; dolor musculoesquelético/miofascial, SDRC	chronic pain; acute pain; neuropathic pain; low back pain/sciatica; migraine/headache; fibromyalgia; arthritis/osteoarthritis; musculoskeletal/myofascial pain, SDRC	Clinical variants and commonly used terms were combined.
Forms of representation	mi historia/testimonio; información clínica; humor/meme; reto/espectáculo; activismo/denuncia.	My story/testimony; clinical info; humor/meme; challenge/performance; advocacy/denunciation.	Terms intended to capture communicative functions.
Complementary/alternative and misinformation signals	remedios naturales; suplementos; detox; cura milagrosa; “100%”; “en 7 días”; “sin efectos”; “los médicos no quieren que sepas...”.	natural remedies; supplements; detox; miracle cure; “100%”; “in 7 days”; “no side effects”; “doctors don’t want you to know...”.	Linguistic markers associated with exaggerated or unsupported health claims.

Panel B. Platform-specific adaptation: queries and operational criteria.

Platform	Search mode	Available filters	Risk of bias	Mitigation applied
Facebook	Text/hashtag search.	Limited by the interface; variable recency.	Relevance ranking and personalization.	Operational quotas; systematic selection of every kth result; avoid clusters from the same author.
Instagram	Text and hashtags.	Variable views; tendency to prioritize popularity.	Bias toward virality and Reels formats.	Alternate views where available; operational quotas; limits by author/dominant hashtag.
TikTok	Text/hashtags; exploration of trends.	Heterogeneous time filters.	Overrepresentation of viral content.	Operational quotas; systematic selection; documentation of restrictions.

Platform	Search mode	Available filters	Risk of bias	Mitigation applied
YouTube	Search by text/tags and channels.	Sorting by relevance/date depending on the interface.	Bias toward large channels.	Systematic selection; diversity of sources; operational quotas.
X	Keyword/hashtag search.	Latest/Top varies by interface.	Bias due to ranking and event timing.	Consistent use of the default view; monthly quota sampling; avoid concentration of authors.

Table S5. Template variable dictionary and eligibility for the de-identified analytical dataset (S5_dataset_analitico).

Field	Type	Domain	Definition	In S5	Sharing notes
record_id	string	Unique	Unique record identifier.	Yes	Untraceable.
Platform	Categorical	5 levels	Content platform.	Yes	-
post_url	String	URL	Link to the original content.	No	Excluded (tracing/ToS risk).
post_id_platform	String	ID	Native platform identifier.	No	Excluded (traceable).
author_anon	String	Code	Anonymized author/profile.	No	Excluded as a precaution; may be retained internally.
date_utc	Date	UTC	Publication date/time.	No	S5 uses year to minimize granularity.
Year	Integer	2021-2025	Publication year derived from date_utc.	Yes	Adjustment variable.
language	Categorical	ES/EN	Predominant language.	Yes	-
text_transcript	Text	long	Text or transcript of audiovisual content.	No	Excluded (re-identification).
media_type	Categorical	text/image/video/mixed	Predominant media type.	No	Optional; not required for the main model.
hashtags	Text	list	Raw hashtags.	No	Excluded (facilitates tracing).
topic_tags	Text	structured	Derived thematic tags.	No	Optional; omit if not used analytically.
rep_form_primary	Categorical	6 levels	Dominant form of pain representation.	Yes	Main predictor.
rep_form_secondary	Categorical	6 levels	Second relevant form (if applicable).	No	Optional/interpretive.
disinfo_present	Binary	Yes/No	Presence of health misinformation.	Yes	Main outcome; 'uncertain' excluded.
disinfo_type	Categorical	5 levels	Misinformation type (if Yes).	Yes	-
source_cited	Binary	Yes/No	Cites at least one verifiable source.	Yes	Covariate.

Field	Type	Domain	Definition	In S5	Sharing notes
source_type	Categorical	5 levels	Type of cited source.	Yes	-
val_empathy_comments_n	Integer	0-50	Empathic comments among the first 50 responses.	Yes	-
val_invalidation_comments_n	Integer	0-50	Invalidating comments among the first 50 responses.	Yes	-
val_support_ratio	Continuous	0-1	$E/(E+I)$; missing if $E+I=0$.	Yes	-
val_support_band	Ordinal	V1-V5	Bands V1–V5 derived from val_support_ratio.	Yes	-
n_views	Integer	≥ 0	Views (if available).	No	Descriptive; heterogeneous across platforms.
n_likes	Integer	≥ 0	Likes at capture.	No	Summarized in S5 as engagement_zcore.
n_comments	Integer	≥ 50	Total comments at capture.	No	Inclusion criterion; not required in S5.
n_shares	Integer	≥ 0	Shares/reposts/retweets.	No	Summarized in S5 as engagement_zcore.
engagement_raw	Derived	≥ 0	$n_likes + n_comments + n_shares$.	No	Intermediate; not essential in S5.
engagement_zcore	Continuous	z-score	Platform-specific z-score of the base index.	Yes	Comparable continuous predictor.
professional_identity_declared	Binary	Yes/No	Professional identity declared by the source.	Yes	Protective covariate.
Professional	Categorical	Variable	Declared profession (if explicit).	No	Only if standardized and used.
safety_disclaimer_present	Binary	Yes/No	Safety/responsible-use warning.	Yes	Covariate/credibility.
coder_id_primary	ID	Code	Primary coder.	No	Metadata; sharing optional.
coder_id_secondary	ID	Code	Second coder (reliability).	No	Metadata; sharing optional.
adjudicated_by	ID	Code	Adjudicator.	No	Metadata; sharing optional.

Field	Type	Domain	Definition	In S5	Sharing notes
adjudicated_date	Date	YYYY-MM-DD	Adjudication date.	No	Metadata; sharing optional.
adjudicated_rep_form_primary	Categorical	6 levels	Final value after adjudication.	No	Metadata; sharing optional.
adjudicated_disinfo_present	Binary	Yes/No	Final value after adjudication.	No	Metadata; sharing optional.
adjudicated_disinfo_type	Categorical	5 levels	Final type after adjudication.	No	Metadata; sharing optional.
notes_free_text	Text	Free text	Coder's internal notes.	No	Excluded (potential re-identification).

Table S6. Reproducibility appendix: package components and analytical traceability.

File	Format	Content	Purpose	Access
README (Reproducibility appendix)	DOCX/PDF	Operational definitions, coding rules, reproducible Stata commands, and integrity checks (e.g., <code>val_support_ratio</code> $\in [0,1]$).	Reproducibility of methods and analyses	Included
Codebook and variable dictionary	XLSX	Codebook (representation, misinformation, social validation, credibility) and variable dictionary with values/codes.	Transparency and replication	Included
Supplementary tables (S1–S11)	DOCX/PDF	Additional study tables: selection flow, coding rules, sensitivity models (<code>val_support_ratio</code> ; V1–V5), bivariate analyses by source type, etc.	Analytical support	Included
Figure S1 (corpus PRISMA)	PNG/PDF	PRISMA diagram of the 2021–2025 corpus (selection and exclusions).	Flow transparency	Included

Note. This appendix describes the materials included for reproducibility; microdata and user identifiers are not distributed. Results are reproduced using the reported Stata commands.

Table S7. Extended logistic model with continuous social validation (val_support_ratio).

Covariate (category)	aOR (95% CI)	p
Form of representation (ref.: Clinical information)		
Activism/denunciation	1.51 (0.16-14.05)	0.716
Spectacle	8.96 (2.87-27.98)	<0.001
Naturopathic/complementary	2.35 (1.16-4.72)	0.017
Meme	1.52 (0.41-5.58)	0.527
Testimonial	0.17 (0.04-0.78)	0.022
Platform (ref.: Facebook)		
Instagram	7.11 (2.76-18.36)	<0.001
TikTok	2.26 (0.88-5.81)	0.092
X	0.42 (0.12-1.44)	0.166
YouTube	0.14 (0.02-0.92)	0.040
Language (ref.: Spanish)		
English	1.00 (0.28-3.65)	0.995
Year (ref.: 2021)		
2022	0.16 (0.04-0.73)	0.018
2023	0.05 (0.01-0.33)	0.002
2024	0.07 (0.02-0.28)	<0.001
2025	0.04 (0.01-0.15)	<0.001
engagement_log_z (continuous)	1.52 (1.06-2.19)	0.023

Covariate (category)	aOR (95% CI)	p
Cited source (ref.: No)		
Yes	0.19 (0.04-0.91)	0.038
Declared professional identity (ref.: No)		
Yes	0.34 (0.16-0.71)	0.004
Thematic hashtag (ref.: #Dolor)		
#Dolorcrónico	0.44 (0.15-1.28)	0.132
#Fibromialgia	0.36 (0.13-1.01)	0.053
#Migraña	0.56 (0.25-1.25)	0.153
val_support_ratio (continuous)	0.0079 (0.0017-0.0373)	<0.001

Note. N=550. Logistic regression with robust standard errors. References: Clinical information; Facebook; Spanish; 2021; #Dolor; and "No" for cited source and professional identity. val_support_ratio is bounded within [0,1] (min.=0.0285714; max.=1).

Stata command: `logistic disinfo_bin i.rep_form_id3 i.platform_id i.language_id i.year c.engagement_log_z i.source_cited_bin i.prof_bin i.hashtags_paper_id c.val_support_ratio, vce(robust)` or

Table S8. Model with social validation bands (val_support_band_id; V1–V5).

Band (ref.: V1)	aOR	95% CI	p
V2	0.3308	0.0756-1.4483	0.142
V3	0.6063	0.1518-2.4215	0.479
V4	0.2644	0.0843-0.8296	0.023
V5	0.0500	0.0165-0.1515	<0.001

Note. N=550. Adjusted logistic regression with robust standard errors (robust variance estimation). Reference category: V1. Adjusted odds ratios (aORs) and 95% confidence intervals (95% CIs) are reported. Stata command: logit disinfo_bin i.val_support_band_id i.rep_form_id3 i.platform_id i.year i.language_id i.hashtags_paper_id, vce(robust)

Table S9. Adjusted predictive margins of misinformation by social validation bands (V1–V5).

Band	Adjusted probability Pr(disinfo_bin=1)	95% CI
V1	0.4735	0.3093-0.6376
V2	0.3036	0.1529-0.4544
V3	0.3941	0.2453-0.5430
V4	0.2727	0.1954-0.3500
V5	0.1025	0.0722-0.1327

Note. N=550. Adjusted predicted probabilities Pr(disinfo_bin=1) estimated using margins after the model in Table S8, with robust standard errors (robust variance estimation). Stata command: margins val_support_band_id

Table S10. Distribution of misinformation by type of cited source (source_type3) and exact test.

Source type (source_type3)	disinfo=0, n (%)	disinfo=1, n (%)	Total
None	399 (80.93)	94 (19.07)	493
Scientific	53 (98.15)	1 (1.85)	54
Institutional/Professional	3 (100.00)	0 (0.00)	3

Source type (source_type3)	disinfo=0, n (%)	disinfo=1, n (%)	Total
Total	455 (82.73)	95 (17.27)	550

Note. N=550. Fisher's exact $p=0.001$. Interpret cautiously because of low counts in categories other than 'None'. Stata command: tab source_type3 disinfo_bin, row exact

Table S11. Alternative model with a binary indicator of source presence (source_any).

Covariate (category)	aOR (95% CI)	p
Form of representation (ref.: Clinical information)		
Activism/denunciation	2.02 (0.29-13.88)	0.476
Spectacle	10.76 (3.44-33.63)	<0.001
Naturopathic/complementary	2.42 (1.25-4.70)	0.009
Meme	1.47 (0.43-4.99)	0.539
Testimonial	0.17 (0.04-0.74)	0.018
Platform (ref.: Facebook)		
Instagram	7.21 (2.98-17.46)	<0.001
TikTok	2.09 (0.88-4.94)	0.093
X	0.61 (0.18-2.04)	0.422
YouTube	0.09 (0.01-0.60)	0.013
Language (ref.: Spanish)		
English	1.27 (0.32-5.03)	0.729
Year (ref.: 2021)		
2022	0.28 (0.06-1.44)	0.128
2023	0.13 (0.03-0.63)	0.011
2024	0.11 (0.03-0.41)	0.001
2025	0.06 (0.02-0.23)	<0.001
engagement_log_z (continuous)	1.79 (1.27-2.52)	0.001

Covariate (category)	aOR (95% CI)	p
Source presence (source_any) (ref.: None)		
Source present	0.20 (0.03-1.43)	0.110
Declared professional identity (ref.: No)		
Yes	0.37 (0.19-0.71)	0.003
Thematic hashtag (ref.: #Dolor)		
#Dolorcrónico	0.39 (0.13-1.12)	0.080
#Fibromialgia	0.35 (0.14-0.91)	0.031
#Migraña	0.56 (0.27-1.16)	0.119

Note. N=550. source_any: 1=Source present (any type), 0=None. This model was included as a robustness analysis because of the low frequency of specific source_type categories and perfect prediction problems in multiclass models.

Stata command: `logistic disinfo_bin i.rep_form_id3 i.platform_id i.language_id i.year c.engagement_log_z i.source_any i.prof_bin i.hashtags_paper_id, vce(robust)` or



7.1 Reproducibility appendix

A1. Scope and unit of analysis

This appendix documents the operational and analytical procedures required to reproduce the study's quantitative results and sensitivity/robustness approach. The unit of analysis is the individual post (post/video/reel/thread). The quantitative component estimates associations (without causal inference) between forms of pain representation and misinformation, adjusting for platform, language, year, engagement, and credibility markers. The qualitative component is based on a stratified subsample linked through record_id.

A2. Data source, platforms, and period

Public content from five platforms was included: Facebook, Instagram, TikTok, X, and YouTube. Posts in Spanish or English published between January 1, 2021, and November 15, 2025, were selected. Capture was manual (2024–2025) and retrospective within the defined window. Threads was assessed only in an expanded scenario and was not included in the main analysis because it did not meet the required interaction threshold (≥ 50 comments).

A3. Search strategy, sampling, and deduplication

Searches used primary clinical terms/hashtags: #dolor, dolor crónico, migraña, and fibromialgia (and their English equivalents: #pain, chronic pain, #migraine, fibromyalgia). Posts were assessed as they appeared in each application's search results. Sampling was nonprobabilistic and dependent on the default algorithmic order. A comparative sample size of 110 posts per platform ($N=550$) was established, with a one-post-per-account rule to reduce dependence on individual sources.

Deduplication: within-platform duplicates (same link/ID when available) and cross-platform duplicates were excluded when the content was clearly reposted or reused material (e.g., the same audiovisual content with minimal editing or the same substantive text attributable to the same source).

A4. Inclusion and exclusion criteria

Inclusion: public content; date within the study period; Spanish or English language; explicit reference to clinical pain; ≥ 50 comments at capture. Exclusion: private profiles; advertising/product sales without substantive content; duplicates; reposts; outside the study period; languages other than ES/EN; non-health-related metaphorical uses of "pain"; broken links; posts with < 50 comments.

A5. Data recording and transcription

Each post was entered into a structured template containing platform, date (UTC), language, media type, text/transcript, interaction metrics (likes, comments, shares; views where available), hashtags, and contextual notes. Transcription, where needed, was manual. Author identifiers were anonymized using alphanumeric codes.

A6. Final variables (exact names used in Stata)

Outcome

- disinfo_bin (1=Yes; 0=No): presence of health misinformation (binary).

How to cite this article / Standard reference: (APA 7th edition)

Barros Beracaza, E., García García, F., Martínez Rodrigo, E. (2026). Pain and Misinformation on Social Media: Digital Representations, Amplification, and Social Validation in Health Communication (2021–2025). *Prisma Social revista de ciencias sociales*, 55, 1-62. <https://doi.org/10.65598/rps.6178>

Main exposures and covariates

- rep_form_id3: dominant form of representation (ref.: Clinical information).
- platform_id: platform (ref.: Facebook).
- language_id: language (ref.: Spanish).
- year: year (ref.: 2021; categorical variable).
- hashtags_paper_id: dominant thematic hashtag (ref.: #Dolor).

Engagement

- engagement_raw = likes + comments + shares
- engagement_log = $\ln(\text{engagement_raw} + 1)$
- engagement_log_z: z-score of engagement_log (continuous).

Credibility markers

- source_cited_bin (1=Yes; 0=No): presence of a verifiable reference (article/technical document; guideline/consensus; health institution with a traceable reference). Generic institutional mentions without an identifiable reference are not considered a “cited source.”
- prof_bin (1=Yes; 0=No): declared professional identity (binary for adjustment). A categorical variable is retained for description (e.g., Physician, Dentist, Pharmacist, Physiotherapist, Massage therapist/Osteopath, Physical therapist, Therapist/psychology, Nutrition, Other, None).

Social validation

- val_support_ratio: social validation index based on the first 50 responses; empathic / (empathic + invalidating). Neutral/unclassifiable comments are included in neither the numerator nor the denominator.
- val_support_band_id: ordinal bands V1–V5 derived from val_support_ratio (ref.: V1).

Multiclass source (descriptive only)

- source_type3: descriptive variable derived from source type (e.g., None vs Scientific vs Institutional/Professional).
- source_any (binary): Source present vs None (for a stable alternative model).

A7. Integrity checks (reproducible checks)

We verified that val_support_ratio remained within [0,1], with no out-of-range values. Examples of reproducible checks:

- count if val_support_ratio < 0
- count if val_support_ratio > 1
- assert inrange (val_support_ratio, 0, 1)
- summarize val_support_ratio, detail

Completeness of analytical covariates was checked, and any reduction in N in alternative models was documented (e.g., when a variable was incomplete across the sample).

A8. Main model specification (M2)

The main model estimates the probability of misinformation adjusted for representation, platform, language, year, engagement, credibility markers, and thematic hashtag, with robust standard errors. Command: `logistic disinfo_bin i.rep_form_id3 i.platform_id i.language_id i.year c.engagement_log_z i.source_cited_bin i.prof_bin i.hashtags_paper_id, vce(robust)` or

Margins (Figures 1–2)

`margins platform_id`

`margins rep_form_id3`

Discrimination (Figure 3)

Discriminatory ability was assessed using the ROC curve and AUC of the main model (M2).

A9. Sensitivity and robustness (prespecified)

1. Continuous social validation (extended model; Table S7)

`logistic disinfo_bin i.rep_form_id3 i.platform_id i.language_id i.year c.engagement_log_z i.source_cited_bin i.prof_bin i.hashtags_paper_id c.val_support_ratio, vce(robust)` or

2. Social validation by bands V1–V5 (Table S8) and margins (Table S9)

`logit disinfo_bin ib1.val_support_band_id i.rep_form_id3 i.platform_id i.year i.language_id i.hashtags_paper_id, vce(robust)`

`margins val_support_band_id`

3. Multiclass source_type3 (Table S10; descriptive). Because of low counts and cells with 0 events (complete separation), source_type3 is reported descriptively with an exact test:

`tab source_type3 disinfo_bin, row exact`

4. Stable alternative model with binary source_any (Table S11)

`logistic disinfo_bin i.rep_form_id3 i.platform_id i.language_id i.year c.engagement_log_z i.source_any i.prof_bin i.hashtags_paper_id, vce(robust)` or

A10. Qualitative subsample and integration

A stratified subsample of N=300 (60 per platform), linked through record_id, was analyzed qualitatively. Thematic analysis was hybrid (inductive–deductive) and documented through analytical reading, standardized analytical memos, and paraphrased evidence. Quantitative–qualitative integration used narrative triangulation.

A11. Ethics and risk minimization

Only public content was used, without interaction with users or collection of personally identifiable data. Identifiers were anonymized, and qualitative evidence was presented as paraphrases to minimize re-identification, following AoIR (2019) recommendations and risk-minimization principles.

