# Analyzing Cultural, Linguistic, and Social Differences in Types of Support in English and Spanish Social Media Comments

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## Abstract

Social support is a multifaceted construct involving emotional, appraisal, informational, and instrumental aid, which individuals derive from their social connections. This study explores how social support is expressed differently by English and Spanish speakers on the YouTube platform, emphasizing cultural and linguistic variations. Annotations of social issues alongside the four types of social support mentioned above were conducted by both human experts and GPT model, demonstrating substantial agreement. A chi-square test confirmed significant differences in the distribution of support types between the two languages. Further linguistic and psychological analysis using LIWC revealed distinct patterns of social processes, affect, and cultural markers associated with each support type across languages. Our findings highlight important cultural nuances in the expression of online social support and demonstrate the utility of advanced NLP tools for cross-linguistic social media analysis. This work contributes to a better understanding and design of culturally sensitive digital support systems.


## 1 Introduction

Social support is usually conceptualized as an emotional, intangible, and tangible aid procured from one's social connections, whereby the person feels loved, cared for, respected, and valued (Kolesnikova et al., 2025; Xia et al., 2012). It is often differentiated into four types of resources:

Social support can be categorized into four main types. *Emotional support* involves expressing care, empathy, love, and trust to provide comfort. *Appraisal support* focuses on offering feedback or validation that aids in self-evaluation rather than solving specific problems. *Informational support* refers to sharing advice or guidance to help someone navigate challenges, especially during stressful situations. Lastly, *instrumental support* entails providing tangible assistance, such as goods, services, or financial aid, to address practical needs (Thomas and Hodges, 2024; Langford et al., 1997).

Social support is a multidimensional construct that encompasses both psychological and material resources available to individuals through their interpersonal relationships (Ahani et al., 2024; Rodriguez and Cohen, 1998). The expression of social support on digital platforms is influenced by various cultural, linguistic, and platform-specific factors. Given the growing importance of social media in facilitating interpersonal support, understanding these factors is essential for enhancing online support dynamics. This research investigates the cultural and linguistic variations in social support expression, specifically focusing on English and Spanish speakers. By leveraging advanced linguistic analysis and natural language processing techniques, In this study, we employed GPT-4o to classify our English and Spanish dataset, which consisted of two binary classification tasks and one multi-class task. Task 1 involved distinguishing between Support and Non-Support, while Task 2 categorized instances as related to either an Individual or a Group. Task 3, a multi-class classification, included the categories Nation, Other, LGBTQ, Black Community, Women, and Religion, alongside the four types of social support discussed earlier (Ahani et al., 2024; Tash et al., 2025). Following classification, we performed an in-depth analysis of the results. Additionally, we utilized LIWC (Tash et al., 2024) to extract various linguistic and psychological categories, including Social Processes, Word Count (WC), Function Words, Affect, Drives, and Culture. The detailed analysis and findings are presented in the following sections.

The following contributions summarize the key findings of this research:

**Cross-Linguistic Analysis of Social Support:** The study provides a comparative analysis of how social support is expressed in English and Spanish on YouTube, revealing key cultural and linguistic differences.

**Human-AI Annotation Synergy:** It demonstrates substantial agreement between human experts and GPT model in annotating social support types, highlighting the reliability of AI-assisted annotation in social media research.

**Statistical Validation of Cultural Variation:** A chi-square test confirmed significant differences in the distribution of social support types between English and Spanish speakers, emphasizing the role of culture in online support behavior.

**Linguistic and Psychological Insights Using LIWC:** The LIWC analysis uncovered distinct linguistic and psychological patterns tied to each type of support, contributing to the understanding of how cultural markers influence online communication.

## 2 Literature Review

Recent studies have focused on the use of NLP techniques for social support detection. Ahani et al. (2024) accomplished the classification of individual vs group support using the fusion of psycholinguistic, emotional, and linguistic features with n-grams, achieving an accuracy of 0.72 to 0.82. Using Transformer models from Hugging Face, Kolesnikova et al. (2025) utilized LLMs (GPT-3, GPT-4, GPT-4-turbo) with Zero-Shot learning. Their research showed that RoBERTa-base was the most effective model, surpassing the other results by up to 8%.

Kwon et al. (2025) investigate the patterns of social support among cancer patients and how these patterns affect their self-reported outcomes using latent class analysis (LCA). The analysis divides social support into emotional, instrumental, informational, and appraisal categories, from which three tiers of latent classes—low, moderate, and high emotional support—are formed. The results demonstrate that social support is not equally proportioned, and possessing strong support in one area does not guarantee that other areas will be well-supported. The study underscores lacking social support and intervention customization for older patients with cancer. Moreover, it proposes social prescribing, which involves referring patients to local community services, as a possible way to fill the support gaps. Choi et al. (2024) investigate the social support phenomenon among nursing students with clinical training using a concept analysis approach. The analysis of 27 selected documents from the years 2000 to 2022 revealed four dimension descriptors of social support: structural (integration into social networks), educational (academic and modeling), psychosocial (emotional and positive appraisal self-esteem), and instrumental (informational and material). Antecedents of social support are classified as stress, personal need, social network, and social climate, while its consequences are improved mental health and enhanced quality of life. Findings indicated that social support in nursing students is composite and multi-faceted in both functional and structural aspects which needs further measurement focus for later studies and more specialized tools for programs and research.

## 3 Methodology

**Datasets**: In this study, datasets outlined in two previous papers (Ahani et al., 2024; Tash et al., 2025) were utilized, focusing on YouTube comments. This research is limited to a single platform and two languages (English and Spanish), selected for their abundant resources to offer an initial analysis. We selected YouTube as the data source because it hosts a wide variety of videos related to special events, enabling the analysis of real-time comments directly associated with supportive responses. This platform offered rich and relevant data aligned with the focus of our research. The support comments were categorized into two tasks: a binary task, which includes group and individual classifications, and a multi-class task, which categorizes group comments based on various social issues such as nationality, the Black community, women, religion, LGBTQ+, and others. Classification was based on social issues, and the categories were the same in both the English and Spanish datasets (Kolesnikova et al., 2025). The comments were also classified according to the type of social support they expressed, including emotional, informational, appraisal, and instrumental support (Langford et al., 1997). For statistical data, please refer to Table 1.

### 3.1 Annotation Guidelines

The social support detection (SSD) task is defined as a single-step classification to identify the type of support expressed in text comments. Each comment is assigned one of the following four support types:

| *Task* | *Category* | *English Count* | *Spanish Count* |
|---|---|---|---|
| Task 1 | Supportive | 2,232 | 678 |
| Task 2 | Group | 1,811 | 507 |
| | Individual | 421 | 171 |
| Task 3 | Nation | 981 | 35 |
| | Other | 519 | 101 |
| | LGBTQ | 154 | 245 |
| | Black Community | 114 | 16 |
| | Women | 24 | 41 |
| | Religion | 19 | 69 |
| Support Type | Emotional | 1,826 | 298 |
| | Informational | 257 | 94 |
| | Appraisal | 128 | 286 |
| | Instrumental | 21 | - |

Table 1: Statistics for English and Spanish Datasets

**Support Type Classification**

- **Emotional Support (ES):**
  Comments that express empathy, care, encouragement, comfort, or reassurance. They aim to alleviate emotional distress.
  *Example:* "I'm here for you." / "Estoy aquí para ti."

- **Informational Support (IS):**
  Comments that provide advice, suggestions, facts, or guidance to help solve a problem or provide useful information.
  *Example:* "Check this helpful article." / "Consulta este artículo útil."

- **Instrumental Support (ISu):**
  Comments that offer tangible help, services, or direct assistance with tasks or needs.
  *Example:* "Let me help you move." / "Te ayudo a mudarte."

- **Appraisal Support (AS):**
  Comments that provide affirmation, feedback, or validation to help the recipient evaluate or interpret their situation positively.
  *Example:* "You did an excellent job." / "Lo hiciste muy bien."

### 3.2 Annotation Process and Inter-Annotator Agreement

The annotation task focused on detecting the type of social support expressed in comments, classifying each comment into one of four predefined categories. **English Dataset:** Two human annotators, co-authors of this paper with PhD and master's degrees, independently labeled the English dataset over seven days following detailed guidelines to ensure consistency and reduce bias. GPT was also used as an automated annotator to compare human-machine agreement. Cohen's Kappa scores were 0.624 (GPT vs. Human 1), 0.841 (Human 1 vs. Human 2), and 0.802 (Human 2 vs. GPT). After label harmonization using a predefined mapping, Krippendorff's Alpha among the three annotators was 0.758, indicating substantial agreement. Final labels were selected based on the highest frequency consensus among annotators.

**Spanish Dataset:** Three annotators participated, including GPT as annotator one, a native Spanish-speaking co-author pursuing a Ph.D., and another native Spanish-speaking Ph.D. student. The third annotator was initially trained with 100 sample examples to clarify guidelines. Cohen's Kappa scores were 0.748 (GPT vs. Annotator 2), 0.930 (Annotator 2 vs. Annotator 3), and 0.676 (GPT vs. Annotator 3). Krippendorff's Alpha for all three was 0.786, indicating substantial agreement. Final labels were chosen by majority consensus across annotators.

### 3.3 Statistical Validation of Support Type Differences

To determine whether the observed differences in the distribution of support types between the English and Spanish datasets were statistically significant, we conducted a chi-square test of independence (Shen et al., 2022). The contingency table was constructed based on the frequency of each support type (Emotional, Informational, Appraisal, and Instrumental) in both datasets.

The chi-square test produced the following results:

- **Chi-square statistic:** 596.46
- **Degrees of freedom:** 3
- **p-value:** $5.89 \times 10^{-129}$

Given the extremely small p-value (well below the conventional threshold of 0.05), we conclude that the differences in support type distributions between the two languages are highly statistically significant. These findings suggest that the variation is not due to random chance but may reflect meaningful cultural or contextual differences in how social support is expressed in English and Spanish content.

### 3.4 GPT-Based Classification

We employed OpenAI's GPT-4o model to classify social support types in English and Spanish datasets (Tash et al., 2025; Imamguluyev, 2023). The model was used via the ChatCompletion API with the parameters: `model=gpt-4o`, `max_tokens=10`, and `temperature=0.2`. A system message instructed the model to classify the text into one of four categories: *Emotional*, *Informational*, *Instrumental*, or *Appraisal* support, based only on the provided text.

For English, the prompt included the following few-shot examples:

```
Text: "I'm really sorry you're going
through this. Stay strong!" -> Emotional
Text: "You can apply for financial aid
through this website." -> Informational
Text: "I can help you move to your new
apartment this weekend." -> Instrumental
Text: "You're doing great! Keep going
and don't give up!" -> Appraisal
```

For Spanish, the structure was identical, but adapted linguistically:

```
Texto: "Lo siento mucho que estés
pasando por esto. ¡Mantente fuerte!" ->
Emotional Support
Texto: "Puedes aplicar para ayuda
financiera a través de este sitio web."
-> Informational Support
Texto: "Puedo ayudarte a mudarte a tu
nuevo apartamento este fin de semana."
-> Instrumental Support
Texto: "¡Estás haciendo un gran trabajo!
¡Sigue así y no te rindas!" -> Appraisal
Support
```

Each comment was evaluated individually by the model, and the predicted support type was stored in a new column. The updated datasets were exported to CSV for further analysis.

### 3.5 LIWC

The LIWC model has significantly advanced psychological research by enabling robust, accessible, and scientifically rigorous analysis of language data. LIWC-22 evaluates over 100 textual dimensions, all validated by respected research institutions worldwide, and has been cited in over 20,000 scientific publications, establishing it as a trusted tool in the field. Additionally, the software supports nearly 15 languages, including English and Spanish (LIWC, 2024). Despite its strengths, LIWC has limitations, such as its reliance on predefined linguistic categories that may not fully capture the complexity of natural language. It also struggles with accurately interpreting sarcasm, irony, and subtle expressions, which can lead to potential misinterpretations (Lyu et al., 2023; Bojić, 2023).

In our analysis, we explored linguistic and cultural differences in online social support by computing the average values for six key LIWC categories—Social Processes, Word Count, Function Words, Affect, Drives, and Culture—across four distinct support types in both English and Spanish comments. These categories were selected for their theoretical and empirical relevance in capturing psychological, emotional, and communicative dimensions of support discourse. This focused yet comprehensive approach allows for meaningful cross-cultural comparisons without introducing excessive dimensionality.

Each category reflects an important facet of communication. Social Processes(Pennebaker et al., 2015) include linguistic cues of human interaction, such as personal pronouns and involvement-related verbs. Word Count (WC) serves as a proxy for user engagement and conversational fluency. Function Words(Baddeley and Singer, 2008) encompass structural elements like pronouns, articles, prepositions, auxiliary verbs, and conjunctions, offering insights into communicative style. The Affect category (Pennebaker et al., 2015) captures emotional expression through subdimensions such as Positive Emotion, Negative Emotion, Anxiety, Anger, Sadness, and Swear Words. Drives(Pennebaker, 2001) reflect underlying motivations, and our analysis focused on Affiliation, Achievement, and Power. Finally, the Culture category(Boyd et al., 2022) includes culturally salient topics such as Politics, Ethnicity, and Technology.

To ensure consistency and comparability, we relied on LIWC's built-in normalization, which calculates each category's percentage relative to the total word count of the text. We then computed average values for each feature in both English and Spanish datasets to address potential imbalances.

These linguistic markers provide valuable insights into the psychological and communicative dimensions of each support type across languages.

## 4 Analysis and Results

### 4.1 Support Types in the English Dataset

The analysis of support types in the English dataset reveals consistent patterns across groups, with notable distinctions in their emphasis on different support types. *Emotional support* emerges as the most prevalent form across nearly all categories. The *LGBTQ* (95.80%) and *Nation* (92.24%) groups exhibit the highest levels of emotional support, high-

| Labels | Emotional | Appraisal | Informational | Instrumental |
|---|---|---|---|---|
| Support | 88.67 | 3.16 | 7.97 | 0.20 |
| Individual | 82.38 | 11.92 | 5.42 | 0.27 |
| Group | 90.09 | 1.17 | 8.55 | 0.18 |
| Black Community | 63.22 | 0.00 | 36.78 | 0.00 |
| LGBTQ | 95.80 | 1.40 | 2.80 | 0.00 |
| Nation | 92.24 | 0.56 | 7.20 | 0.00 |
| Other | 90.81 | 1.92 | 6.62 | 0.64 |
| Religion | 70.59 | 0.00 | 29.41 | 0.00 |
| Women | 71.43 | 14.29 | 14.29 | 0.00 |

Table 2: Distribution of Support Types in the English Dataset (in percentages)

lighting a strong emphasis on emotional connection and solidarity. *Group* (90.09%), *Other* (90.81%), and *Support* (88.67%) also show high emotional expression, indicating that empathetic responses dominate support communication in these contexts.

*Appraisal support*, which involves evaluative feedback and affirmation, is generally minimal across most groups. However, *Women* (14.29%) and *Individual* (11.92%) categories show the highest values in this type, suggesting a relatively greater need for validation and self-evaluation in more personalized or gender-related contexts.

*Informational support* varies notably across communities. The *Black Community* stands out with the highest proportion (36.78%), indicating a substantial emphasis on knowledge exchange and practical guidance. *Religion* (29.41%) also reflects a strong inclination toward sharing information and advice. *Women* (14.29%), *Group* (8.55%), and *Support* (7.97%) exhibit moderate levels of informational support, while *LGBTQ* (2.80%) and *Nation* (7.20%) show comparatively lower values.

*Instrumental support*, which entails tangible aid or assistance, remains the least represented across all categories. Most groups—*LGBTQ*, *Nation*, *Black Community*, *Religion*, and *Women*—register 0% in this category, indicating that practical help is rarely offered in this dataset. The few exceptions include *Other* (0.64%), *Individual* (0.27%), *Support* (0.20%), and *Group* (0.18%), although these values are negligible.

Overall, the data suggest that emotional support is the dominant form across English-speaking groups, with variations in informational and appraisal support reflecting the cultural, identity-based, and contextual needs of each group. Instrumental support is virtually absent, reaffirming the primarily emotional and informational nature of online social support interactions in this setting.

### 4.2 Support Types in the Spanish Data set

The analysis of support types in the *Spanish dataset* reveals important patterns in how different communities express and receive support. *Appraisal support*, which involves evaluative feedback or validation, is the most dominant type across several groups. Notably, *Women* (70.73%), *Black Community* (62.50%), and *Other* (56.44%) exhibit the highest levels of appraisal support, suggesting a cultural emphasis on affirming identity and encouraging reflection. Similarly, *LGBTQ* (44.49%), *Group* (43.39%), and *Support* (42.18%) also rely heavily on appraisal support, highlighting its broader relevance across contexts.

*Emotional support* remains significant, particularly in the *Nation* category (82.86%), followed by *Individual* (60.82%), *Support* (43.95%), and *LGBTQ* (43.27%). These values point to a continued reliance on empathy and emotional connection in Spanish-speaking social media interactions, especially in national and personal contexts.

*Informational support* is much less prevalent overall but plays a critical role in specific communities. The *Religion* category stands out with the highest proportion (72.46%), indicating a strong focus on sharing knowledge or guidance in faith-based interactions. The *Black Community* (25.00%), *Group* (18.34%), and *Support* (13.86%) also show moderate levels of informational support. In contrast, *Nation* and *Women* groups receive no informational support (0.00%), and *Individual* shows only a minimal amount (0.58%).

In summary, the data illustrate how Spanish-speaking communities prioritize different types of social support depending on identity and context. *Appraisal support* is the most widespread, particularly among marginalized or personal groups such as *Women*, *Black Community*, and *Individual*, while *Emotional support* plays a dominant role in national and interpersonal scenarios. *Informational support*, although less common, emerges as crucial in religious and culturally specific contexts. These patterns underscore the culturally embedded ways Spanish-speaking users seek and provide social support on digital platforms.

### 4.3 Comparison of Social Support Types in English and Spanish

The primary difference between English- and Spanish-speaking communities in social support types lies in the *higher prevalence of appraisal*

| Label | Appraisal | Emotional | Informational |
|---|---|---|---|
| Support | 42.18 | 43.95 | 13.86 |
| Group | 43.39 | 38.26 | 18.34 |
| Individual | 38.60 | 60.82 | 0.58 |
| Black Community | 62.50 | 12.50 | 25.00 |
| LGBTQ | 44.49 | 43.27 | 12.24 |
| Nation | 17.14 | 82.86 | 0.00 |
| Other | 56.44 | 34.65 | 8.91 |
| Religion | 13.04 | 14.49 | 72.46 |
| Women | 70.73 | 29.27 | 0.00 |

Table 3: Distribution of Support Subtypes Across Tasks (in percentages)

| | English | | | | Spanish | | |
|---|---|---|---|---|---|---|---|
| | Emotional | Appraisal | Informational | Instrumental | Emotional | Appraisal | Informational |
| WC | 18.36 | 18.53 | 30.35 | 17.05 | 11.49 | 28.44 | 85.91 |
| Function Words | 0.31 | 0.22 | 0.13 | 0.33 | 1.49 | 2.30 | 2.52 |
| Social Processes | 5.43 | 5.37 | 4.67 | 7.86 | 2.08 | 3.11 | 3.15 |
| Affect | 6.43 | 5.42 | 3.57 | 5.13 | 5.77 | 2.44 | 1.50 |
| Drives | 4.07 | 6.95 | 6.95 | 9.27 | 7.34 | 6.72 | 6.14 |
| Culture | 1.67 | 0.85 | 3.46 | 2.49 | 0.79 | 0.45 | 5.03 |

Table 4: LIWC feature comparison across support types in English and Spanish

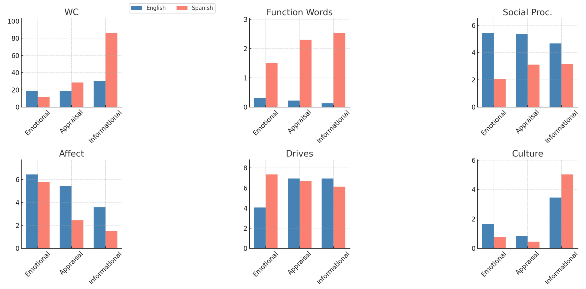


Figure 1: English vs spanish LIWC Feature Comparison by Support Type

*support in Spanish contexts* and the *greater emphasis on informational support in English contexts*. In the Spanish dataset, appraisal support is notably dominant, especially among *Women (70.73%)* and *Black Community (62.50%)*, whereas in the English dataset, the highest appraisal category—*Women*—reaches only *14.29%*. This suggests that *Spanish-speaking cultures place a stronger emphasis on feedback, affirmation, and collective reflection*, consistent with *familismo*—a cultural trait emphasizing strong family and community ties (Campos et al., 2014). In contrast, *English-speaking communities, particularly the Black Community (36.78%)*, show a stronger tendency toward informational support, indicating a more *individualistic approach* where acquiring knowledge and resources is essential for empowerment and self-reliance.

Another prominent distinction is that *emotional support is more evenly and consistently distributed in English-speaking groups*, whereas *Spanish-speaking communities exhibit a wider variation across support types*. In the English dataset, emotional support frequently exceeds *80%*, such as in *LGBTQ (95.80%)*, *Nation (92.24%)*, and *Group (90.09%)*, reinforcing the idea that *empathy and emotional validation are central to supportive communication* in these communities. In contrast, emotional support in the Spanish dataset is more context-dependent. For example, the *Nation* group receives *82.86%* emotional support, while the *Religion* (14.49%) and *Women* (29.27%) categories show much lower values. This suggests that in Spanish-speaking contexts, *emotional reassurance may be embedded within or replaced by appraisal support*, indicating a culturally distinct integration of supportive communication.

These linguistic and cultural contrasts are further reflected in the LIWC feature distribution (Table 4). For instance, informational support in Spanish contexts is associated with significantly higher *Word Count (85.91)* and *Culture (5.03)* scores, suggesting that detailed, context-rich language is more prevalent when sharing advice or knowledge. Conversely, English informational support aligns with relatively high *Word Count (30.35)* but also shows increased *Affect (3.57)* and *Culture (3.46)*, indicating a blend of factual and emotional elements. These findings illustrate how *linguistic and cultural norms shape the way social support is communicated across different languages and communities online*. In Fig. 1, you can find a comparison of English vs. Spanish LIWC features by support type.

## 5 Discussion

Our findings reveal distinct patterns in how social support is expressed across English and Spanish online communities. The significant statistical differences in support type distributions suggest that cultural and linguistic norms shape how people offer help in digital interactions. English comments contained more emotional and informational support, while Spanish comments included a notably higher proportion of appraisal support. This may reflect a culturally driven emphasis in Spanish-speaking contexts on affirming social identity and relational validation.

The integration of GPT-4o enabled scalable and consistent classification of support types, with high inter-annotator agreement confirming the reliability of the labels. GPT-4o's performance in both English and Spanish also indicates its adaptability for cross-linguistic NLP applications, though slightly lower agreement scores with human annotators in Spanish highlight the continued need for culturally grounded annotation practices.

Furthermore, LIWC analysis provided valuable psychological and linguistic insights. For instance, the usage of social processes and function words varied between languages, pointing to underlying communication styles and norms. These variations should inform the design of support-aware NLP tools to ensure language-sensitive performance and cultural fairness.

## 6 Conclusions and Future Work

This study presents a cross-cultural analysis of social support expressed in English and Spanish YouTube comments using GPT-4o for classification and LIWC for linguistic and psychological feature analysis. By categorizing social support into four types—Emotional, Informational, Instrumental, and Appraisal—we demonstrated that cultural and linguistic context significantly influences how support is articulated online.

Our experiments revealed statistically significant differences in support type distributions between English and Spanish, with emotional support dominating both datasets but varying in frequency and style. The chi-square test confirmed these differences were not due to chance, highlighting the role of culture in shaping online supportive behavior. Furthermore, through multi-class classification, we explored how different social groups (e.g., Women, LGBTQ, Religion) are represented in support discourse, providing deeper insights into the social dimensions of support.

The integration of GPT-4o with annotated examples enabled effective classification across languages, while LIWC analysis uncovered distinct psychological and functional word patterns that reflect cultural nuances in communication. Our findings contribute to the growing body of research on digital empathy and cross-cultural NLP by offering evidence of language-specific expressions of care, validation, and aid.

For future work, we propose expanding the study to include additional languages and cultural contexts to test the generalizability of our findings. We also suggest incorporating data from other platforms such as Reddit, which hosts a wide range of community-driven and support-focused discussions, offering a complementary environment to YouTube. Additionally, increasing the size of the dataset and working toward a more *balanced distribution of support types* will be crucial to ensure robust analysis and improve model performance across underrepresented categories. Finally, we recommend interdisciplinary collaborations with social psychologists to deepen the interpretability of cultural patterns and inform the development of culturally sensitive NLP systems.

## 7 Limitations

Despite its contributions, this study has several limitations. First, the dataset is restricted to two languages—English and Spanish—which limits the generalizability of our conclusions to other linguistic and cultural contexts. Second, while LIWC provides valuable psycholinguistic insights, it is constrained by predefined lexical categories and may not fully capture implicit or culturally specific expressions of support. Finally, because our analysis was conducted on YouTube comments, platform-specific norms may influence user behavior, and results may not generalize to other social media environments.

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