

Supportive but Sparse: Cross-Cultural Responses to Mental Health Disclosure on Social Media

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Abstract

Individuals struggling with mental health challenges turn to social media platforms to seek support due to the in-person stigmatization of the topic across different cultures. While researchers have studied the social support users receive on forums specifically designed for mental health support, less is known about the support users seek on open-ended platforms such as X (Twitter). How do these support mechanisms differ across cultures? Through quantitative and qualitative analysis, this work explores variations in social support across seven countries and two regions—the Global North and Global South. We find that users in the Global North and Global South express their support differently. Users in the Global South receive a significant increase in comments on their mental health disclosure posts compared to their non-disclosure posts. With the exception of Australia and India, users tend to maintain consistent posting behavior after disclosure. Overall, users receive scarce engagement on both their disclosure and non-disclosure posts regardless of their region and country.

CCS Concepts

• Human-centered computing → Empirical studies in collaborative and social computing; Empirical studies in collaborative and social computing.

Keywords

Cross Culture, Support, Mental Health, Depression, Social Media, X, Disclosure

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1 Introduction

Mental health is a pervasive issue across the globe, with 1 in 8 people worldwide living with some form of mental disorder [WHO

2022]. Various factors impact how mental health behaviors influence an individual's life, including access to quality therapy and social circumstances such as support and participation [CDC 2024; Hynie 2018; Kirkbride et al. 2024; Pflum et al. 2015]. Because mental health remains a highly sensitive and stigmatized topic [Chancellor et al. 2019; Robinson et al. 2019], many individuals, faced with limited access to proper care, frequently turn to forums and social media platforms to seek support online [De Choudhury et al. 2014; Pretorius et al. 2019; Rayland and Andrews 2023]. Understanding the social support users receive on these platforms is valuable for informing platform design to better facilitate support mechanisms and educating the public about the types of support available online, ultimately creating a more welcoming environment for individuals who reveal their mental health status and seek assistance in digital spaces.

Support mechanisms can be different depending on the culture [Taylor et al. 2007; Zheng et al. 2021] and platform [Rayland and Andrews 2023]. Cultural consideration are crucial in how users express their support to users struggling with mental health issues and are seeking support [Pendse et al. 2019]. For instance, on online forums that are designed for users to seek mental health support, users across cultures use varying language, and provide their support differently [Pendse et al. 2019]. Other open-ended platforms, such as X (Twitter), are a popular venue where users disclose their mental health status [Chancellor and De Choudhury 2020]. However, there's little understanding of the type of support users receive on these platforms and what these support mechanisms look like when users are seeking support in different cultures.

In this work, we ask,

RQ1: What kind of support do users get when disclosing their mental health status on X (Twitter)? Do the types of support users receive vary across cultures or countries?

RQ2: How does social support affect users' posting behavior in the long term?

We answer these questions at both the regional level (Global North vs. Global South) and within each country, where the levels of mental health stigmatization [Krendl and Pescosolido 2020] and usage of the platform are different [World Population Review 2024].

We compare the cultural differences in social support for posts disclosing mental health status and their control counterpart using a cross-culturally annotated dataset spanning seven countries (Australia, UK, US, India, Philippines, Nigeria, and South Africa) across five continents [Abdelkadir et al. 2024]. We applied sentiment analysis and qualitatively analyzed the responses to study the types of support users receive and compare them to the control sets for each country. To validate these findings, we use a benchmark depression dataset curated without regard for country of origin. We apply

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similar analytical methods to both disclosure and non-disclosure posts from users globally.

We found users from the Global North and Global South express their social support to mental health disclosure posts differently. Users in the Global North show their support through likes, whereas in the Global South, through comments. Disclosure posts in the Global South receive a significant increase in comments compared to their control (non-disclosure) counterparts. At the country level, users from the Philippines and the United Kingdom receive significant support in their disclosure posts. In contrast, we see a significant drop in comments for disclosure posts in Australia. In terms of positive sentiment comments, users from all regions and countries receive more positive comments compared to non-disclosure posts except for South Africa and India (where non-disclosure posts received more positive comments). Looking at the long-term impact on users posting behavior pre and post disclosure posts, we find that users in both regions continue posting consistently for three months. However, for Australia and India users tend to drop in their posting behavior – likely impacted by the significant decrease in comments and likes to disclosure posts in each country, respectively. Assessing comments to posts users make three months pre and post their disclosure post, we found users in all countries (except the UK and Nigeria) tend to get similar engagement to their posts even after disclosing their mental health status. Overall, users receive scarce engagement to both disclosure and non-disclosure posts regardless of their country and region.

In summary, we found that users express their social support to mental health disclosure posts differently in the Global North (increase in likes) compared to the Global South (increase in comments). In the long term, we find that users' posting behavior is not significantly affected after making the disclosure post. Regardless of the post status (disclosure or non-disclosure), users from all countries receive scarce engagement. We provide implications for social media platforms and users seeking social support on social networks in these countries.

2 Related Work

Research on social media and mental health has primarily focused on identifying users exhibiting various mental health behaviors (such as depression, suicidal thoughts, and eating disorders) through their online interactions on platforms like X (Twitter) and Reddit [Chancellor and De Choudhury 2020; Montejó-Ráez et al. 2024; Skaik and Inkpen 2020]. Efforts in the domain leverage various interaction modalities, including users' text posts, images, and social interactions, aiming to identify vulnerable individuals with increasing accuracy [Garg 2023; Liu et al. 2022; Wongkoblap et al. 2017].

In addition to these detection mechanisms, cultural considerations of disclosure mechanisms and social support mechanisms online have also been studied [Durvasula and Mylvaganam 1994]. Users culture and gender have an impact on how users disclose their mental health status [De Choudhury et al. 2017]. Users in different communities express their struggles and seek support differently [Casado et al. 2002; Mittal et al. 2023]. Users across cultures on structured online forums also provide support differently [Pendse et al.

2019; Pruksachatkun et al. 2019]. Interactions between users on forum boards such as 7Cups¹ and Talklife² in non-western countries tended to have different styles of communication in comparison to sets of global posts. These studies primarily focus on disclosure behaviors on X (Twitter) and support mechanisms on structured online forums that are primarily designed for users to seek support.

In the case of open-ended platforms, the support mechanisms on Instagram show that users receive positive responses and supportive reactions when communicating their mental health status [Andalibi et al. 2017]. On other platforms, such as Facebook, studies have found that users feel comfortable disclosing negativity but as a result are liked less than users who tend to make more positive posts [Forest and Wood 2012]. Studies have shown that users who are struggling with their mental status turn to X (Twitter) to seek support [Park et al. 2013] or hint at their status on social media as a low stakes way of seeking support [Andalibi et al. 2018]. However, there is little understanding of the kind of support users receive across cultures when revealing their sensitive mental health status on open platforms such as X (Twitter), a platform widely studied in the mental health disclosure domain [Chancellor and De Choudhury 2020], and the cultural differences of support in such open ended platforms. We add to this line of work by exploring the cross-cultural support mechanism at the open platform X, the most widely studied platform in the domain of mental health disclosure on social media [Chancellor and De Choudhury 2020]. We further our understanding of cultural support in seven countries across five continents by examining the responses to mental health disclosure and non disclosure posts.

3 Method

3.1 Datasets

The datasets we used were various collections of posts scraped from X (Twitter). We opted to use the platform as a data source because 1) it is the most widely studied platform in the domain [Chancellor and De Choudhury 2020]. 2) User's geographic location or culture can be inferred from the user's posts, and there is a culturally labeled mental health dataset. In this section, we provide the details of the datasets used.

Cross-Cultural Dataset this is a culturally annotated depression dataset curated by [Abdelkadir et al. 2024]. Users are labeled as either depressed or control (not depressed) through manual annotation inferred from their disclosure post. The data includes users from seven countries across five continents (Australia, the United Kingdom, the United States, India, the Philippines, Nigeria, and South Africa). We gather the engagements or reactions (i.e., comments, likes, quote posts, and re-posts) to both the genuine disclosure and the control posts from the users in each country on the dataset. To get a balanced comparison of support engagement, we balance the number of genuine disclosure vs control posts. See table 1.

Multi-Task Learning Dataset (MTL-D) this dataset introduced by [Shen et al. 2017] contains 1,840 labeled as depressed and 1,840 control users. Similar to the Cross-Cultural dataset, we gather the

¹<https://www.7cups.com/>

²<https://talklife.co/>

engagements to the genuine disclosure post and a randomly sampled post from the control users' posts. See table 1.

Long Term Effect Data to assess the differences in reaction to users posting about their mental health and the long term effect on the users posting behavior, for each user, we randomly sample a post three months before and after posting their mental health status disclosing post³. Specifically, we sample a post the user has made in a 70-100 day range. For the sampled post, we gather the engagement the post received (i.e., comments, likes, quote posts, and re-posts). This data allows us to assess whether the support behavior/engagement changes after a user discloses their mental health status. To assess whether a user's posting behavior changes after their disclosure post, we gather the statistics of their posting behavior three months after their disclosure post.

As the (X) Twitter Research API is defunct, we used Nitter⁴, a website that recreates as much of X as it can without the restriction of having to log in to access posts.

Dataset	Category	#Users	#Posts
Cross Cultural	Depression	267	274
	Control	264	274
MTL-D	Depression	1,840	3,276
	Control	1,840	2,810

Table 1: Datasets used in our experiment.

3.2 Approach

Once all of the comments were retrieved, we calculated the average and sum for the number of comments, likes, retweets, and quotes for each set. For each country, the amount of posts from the non-disclosure dataset was sampled similarly to the number of posts collected in the disclosure dataset. To understand thWe conducted the following three quantitative and qualitative analysis:

- (1) **Sentiment Analysis** sentiment analysis was conducted using Pérez et al. [2024] sentiment model and [Tabularis 2024] multi-lingual sentiment model.⁵ When conducting our sentiment analysis we sampled a similar size of comments from both the disclosure and non-disclosure posts. The models classify posts into three sentiment groups: Positive, Neutral, and Negative.
- (2) **Qualitative Analysis** to further understand the reactions (specifically, comments) to the disclosure and non-disclosure posts, we conducted a qualitative analysis, where we analyzed the comments to understand the support behavior of each country. This process further confirms the tone of the reactions for the posts, the sentiment analysis was not able to identify accurately.

³We opted for three months as the effect of support may be negligible afterwards

⁴nitter.net

⁵There is a slight code-mixing in the cross cultural dataset [Abdelkadir et al. 2024], hence, some of the comments could also be code-mixed. Therefore, we use a multi-lingual sentiment analysis model.

- (3) **Topic Modeling** to find the general topics discussed within the comments we conducted a topic modeling analysis using the LDA topic modeling⁶. However, the topic modeling was only effective for comments in the United States and the United Kingdom due to the sparse data in the other countries.

The long-term effects on users' posting behavior and changes in support were examined by analyzing engagement patterns three months before and after their mental health disclosure. This analysis assessed differences in engagement metrics (comments, likes, quote posts, and re-posts) and changes in positive sentiment comments. Both social support and long-term effect analyses were conducted at regional levels—comparing the Global North (US, UK, Australia) with the Global South (Nigeria, South Africa, India, and the Philippines)—as well as at the country level. We opted for this regional categorization, as countries in these two regions exhibit cultural differences besides the primary metric (economic development) [Braff and Nelson 2022].

Finally, all the comments were preprocessed to remove punctuation, numbers, symbols, and put in lower case before the sentiment analysis and topic modeling.

4 Findings

Dataset		Comments		Likes	
		D	ND	D	ND
Country	Australia	0.17*	1.43*	1.34	4.27
	India	0.4	0.8	0.4*	11.2*
	Nigeria	0.6	0.2	1.07	0.6
	Philippines	0.45*	0.19*	0.71	1.53
	South Africa	0.48	0.27	0.79	1.7
	UK	0.63*	0.2*	7.69	2.32
	US	0.33	0.31	6.88	3.17
Region	Global North	0.37	0.47	6.15	3.16
	Global South	0.47*	0.30*	0.74	2.85
Global	MTL-D	0.31*	0.19*	0.75*	0.63*

Table 2: Reactions to disclosure and non-disclosure (control) posts for each country and region. * represents statistical significance (p-value < 0.05). D stands for disclosure and ND stands for non-disclosure.

4.1 Social Support

We analyze the social support users receive using the rate of comments and the number of likes on their posts. We found that users from the Global North and the Global South tend to express their support towards mental health disclosure posts differently. We found a statistically significant increase in the amount of comments users receive in the Global South. While mental health disclosure posts in the Global North receive lower support in terms of comments, users receive increased support in terms of likes. The users

⁶<https://pypi.org/project/pyLDAvis/>

in the UK, however, saw a significant increase in the number of comments they received when making a disclosure post in addition to the increase in number of likes. These changes can be seen in Table 2. This shows variation in how users in the Global North vs Global South express their support when users disclose their mental health status.

Users receive more positive comments when they make mental health disclosure posts compared to control (non-disclosure) posts, except for India and South Africa (see Table 3). Although this increase is statistically insignificant. However, the disclosure posts in the global MTL-D benchmark dataset see a significant increase in positive comments. Qualitatively analyzing the comments, the users from the Philippines receive more positive and supportive responses for both the disclosing and non-disclosing posts, showing the supportive culture regardless of the user's mental health status. Whereas the South African posts receive comments focused on discussion instead of positive support.

Overall, we found users receive very sparse engagement (replies, retweets, quote-tweets, and likes) to their disclosure post (see table 9). In total, the disclosure posts received 5 comments compared to 184 in the non-disclosure posts. This low engagement is consistent for every country, regardless of the region. A comprehensive country-specific analysis with granular insights is presented in section 4.3.

	Dataset	Disclosure	Non-disclosure
Country	Australia	2	1
	India	2	3
	Nigeria	3	2
	South Africa	3	5
	Philippines	8	4
	UK	12	11
	US	14	9
Region	Global North	28	21
	Global South	16	14
Global	MTL-D	367*	138*

Table 3: Number of positive sentiment analysis classifications [Pérez et al. 2024]. * indicates statistical significance of p-value < 0.05.

4.2 Long-term Effects

We assess the long-term effect by looking at how users' posting behavior changes in the three-month range before and after their disclosure post. We find that users' posting behavior is not significantly affected after making the disclosure post. We see that users in both the Global North and Global South tend to keep a similar posting rate on the platform pre and post their disclosure post, for at least one month. See figure 1 (Global North) and 2 (Global South). However, for Australia and India users tend to drop in their posting behavior – likely impacted by the significant decrease in comments

and likes to disclosure posts in each country, respectively. See figure 3 (Australia) and 4 (India).

We also assess the reactions users receive to their posts pre and post-three months of the disclosure. We find a statistically insignificant difference in the number of comments they receive for these posts (see table 4). However, users in the Global North countries (UK and US), and Global South countries (Nigeria) tend to get less comments on their disclosure posts (although these differences are insignificant). The overall behavior for users to continue to keep posting at similar rates is supported by the findings in section 4.1, where we found that users tend to get varying forms of support in terms of comments and likes, and the positivity of these comments with the exception of Australia and India.

4.3 Country Level Analysis

4.3.1 Australia: The disclosure posts receive significantly fewer comments than their control (non-disclosure) counterparts (see table 2). Similarly, this kind of lower engagement can be seen in the decrease of likes the disclosure posts receive. However, despite the decreasing number of comments, these fewer comments are increasingly positive and supportive in their content. Example of supportive comments include *"I think your amazing, being so strong for everyone. You lost your brother. I'm just one irrelevant person who just loved Chester and Linkin Park in a small town in Australia. Thankyou [6 blue heart emojis]"*. In long term effects, users receive a slightly increased number of comments 3 months post their disclosure (see table 4). While the users get supportive comments, their scarcity compared to the non-disclosure post in the country could be a reason why the posting rate of the users decreases slightly after the disclosure post (see figure 3 in the appendix).

4.3.2 India: Users in India who disclose their mental health status receive lower comments for their disclosure posts compared to users posting non-disclosure posts. This low support is also seen in the significant reduction in likes to disclosure posts. Each comment was classified evenly as positive or neutral. This varied from the non-disclosure set, which was classified as primarily positive in the sentiment analysis. The dataset of disclosure posts from users in India was small, containing only 15 posts in all, which could explain the low response rates. The responses were very few and very short, all of them being only a few words, such as *"Good Morning [blushing smiling emoji]"* and *"whyyy??"*. The lack of responses could be seen as individuals in India not receiving much support when displaying that they are struggling. In the samples taken from 3 months before and 3 months after the disclosure, users overall tended to receive more comments after the disclosure compared to before but this difference in responses was not classified as significant (see table 4). Users in India also tended to post slightly less after the disclosure post (see figure 4). This can be attributed to the lower level of engagement with the disclosure posts in terms of both comments and likes.

4.3.3 Nigeria: While insignificant, users in Nigeria receive more comments and likes on their disclosure posts compared to the control (non-disclosure) posts. The comments to disclosure posts are primarily classified as neutral or positive, and the non-disclosure set was primarily neutral, but when reading through the comments

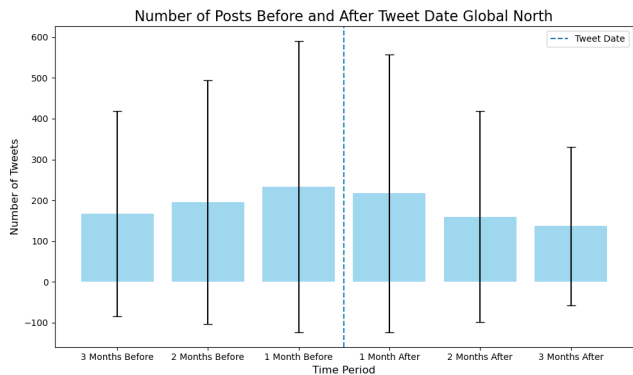


Figure 1: Number of posts made before and after genuine disclosure post in the global north

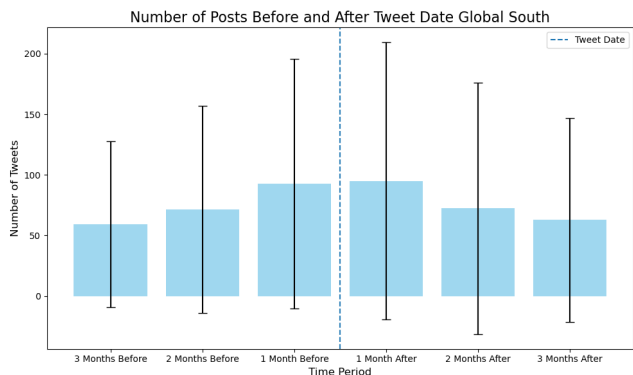


Figure 2: Number of posts made before and after genuine disclosure post in the global south

for the non-disclosure set, there were a higher number of aggressive and negative posts than in other sets. Many more of the responses seemed to be part of arguments or were focused on putting down the original poster. One such example being "If you want links, do your research. Not going to spoon feed you, no matter how much you cry. Go and Verify.". These aggressive responses were not present in the disclosure set, and the amount of supportive or encouraging posts increased. In the longer-term effect, users received fewer comments on their posts three months post the disclosure post (see table 4). In the months following the disclosure post users tended to post more (see figure 5).

4.3.4 Philippines: The social support for the users in the Philippines who disclose their mental health status significantly increases in terms of comments (see table 6). These comments towards these disclosure posts were classified as extremely positive, whereas the non-disclosure posts contained more neutral responses. However, these comments still contained more positive posts than the other cross-cultural posts. Some examples of supportive and positive posts include: "Pssst. You are stronger than you think you are. Rest then arya ulit! [3 kissing emojis][hug emoji] Mwaaah! [3 prayer emojis]" This positivity aligns with the increased comments received

three months post their disclosure (see table 4); however, users did not increase their posting behavior in the next three months after their disclosure post 7).

4.3.5 South Africa: Users in South Africa do not see an increase in social support. While the rate of comments increases in the disclosure set from the non-disclosure set, there are less positive and supportive posts. However, when qualitatively analyzing the set, there were fewer negative comments in the disclosure set. Supportive comments were still present in the disclosure set, but in comparison to other countries or the global set there were many more posts that discussed the issue brought up by the original poster instead of focusing on offering encouragement and support, for example "I hear you sir. But I personally think this issue is way bigger than Twitter. The guy was lonely outside of this app." The content of the posts in non-disclosure set was similarly very neutral and conversational with the occasional argumentative or encouraging post. This could show that the lack of support in the genuine disclosure comments is not indicative of a negative response to users seeking out support, but rather aligns with the general social media presence that users from South Africa maintain. The responses to users after the disclosure post increased but the number of posts the user made remained consistent.

4.3.6 United Kingdom: Users in the UK saw a significantly more social support (in comments) when disclosing their mental health status. Users also received more likes for their disclosure posts compared to the control (non disclosure) ones, even though they were insignificant (see table 2). The majority of the comments on the disclosure posts were classified as positive. Many of these posts many offered help or thanked the original poster for sharing their story. The prevalent topics discussed in the comments towards the disclosure post include *Love, share, story, heart emoji, and talk*. The general trend within these terms suggest many of the comments offered help or support to the original poster. The comments in the UK non-disclosure set were primarily neutral, showing that support increases when users make a mental health disclosure post. On the other hand, users received less comments three months after making their disclosure post (see table 4). However, one month following their disclosure post, users posted slightly more on the platform (see figure 8).

4.3.7 United States: Although insignificant, users received more support (in likes) while the comment rate remained primarily the same (see table 2). Users received more positive sentiment comments towards the disclosure post (see table 3). Relative the other countries, users received short comments. The comments tend to commiserate with the users who are disclosing their mental health status. Examples of responses include: "Lol me" or "Honestly same.". Users received a similar number of comments for their posts three months before and after their disclosure post (see table 4). However, users posting tended to post slightly less on the platform in the months following their disclosure post (see figure 9).

5 Implications

Users in both the Global North and Global South express their support in different ways when reacting to disclosure posts. Users in the Global North tend to receive more likes in response to their

Country	Av. Before	Av. After
Australia	0.21	0.24
India	0.08	0.17
Nigeria	0.36	0.14
Philippines	0.18	0.35
South Africa	0.10	0.26
UK	0.26	0.13
US	0.18	0.17

Table 4: Average amount of comments users receive on posts three months before and after disclosure post; none of the differences were found to be significant.

disclosure posts while users in the Global South tend to receive more comments. So, platforms should adjust to facilitate beneficial forms of communication for users from different cultures. In this case, forums such as 7Cups, TalkLife, and Reddit can be effective in communities that are more oriented towards discussion about mental health. Such platforms are predominantly used in the Global North, however, these comment based communication could be an effective way for platforms to extend their reach to users in the Global South where users may receive more support from their communities. This suggestion is in line with findings from [Pendse et al. 2019] who found that users tend to support others from the same country and provide positive responses. These forum boards are already used in countries such as India and the Philippines but countries such as Nigeria or possibly South Africa may benefit from them as well.

Users should expect the kind of support typical to their country when making mental health disclosures. For example, users from the Global North should expect likes in reaction to their mental health disclosure posts while users in the Global South should expect comments in response. Keeping expectations in mind can be an important tool for managing mental health, particularly in individuals who are already struggling. Users across all countries should also expect lower forms of engagement and reaction to their posts. These expectations can help users determine whether or not they need to seek other avenues of support and health care providers to engage with when seeking to improve their personal mental health faculties.

Further we encourage users from countries where they receive positive support to continue posting. Specifically, for users in the Philippines and UK users receive a significant increase in comments as well as more positive comments when making a disclosure post. However, users in countries such as Australia, South Africa, and the US may need to seek out other avenues of support. Users in Australia receive significantly less comments and the amount of likes decreases as well. The responses they do receive are supportive but the amount of posts the user makes after the disclosure post decreases slightly which could imply a negative effect from the lack of reactions, see figure 3 in appendix. In South Africa and the US users tend to receive more reactions but the responses they receive typically do not focus on supporting the user.

6 Conclusion

In general, users from the Global North and Global South express their social support to individuals disclosing their mental health status in different forms. Users more often like disclosure posts in the Global North whereas comments are utilized in the Global South. We see a significant increase in comments in the Global South. At the country level, the Philippines and the United Kingdom users receive a significant increase in their disclosure posts. In the long term, we find that users' posting behavior is not significantly affected after making the disclosure post. Throughout all regions and countries, disregarding the post's status, users receive low levels of engagement with their posts on the platform. We provide implications to mental health forums to consider expanding their base to the Global South where users tend to show support through comments, and for users to set their expectations in line with the support mechanisms in their respective regions.

Country	Total Posts	Posts Used	Total Users
Australia	40	31	23
India	20	16	14
Nigeria	20	16	11
Philippines	63	44	40
South Africa	39	31	28
UK	59	42	35
US	139	122	51

Table 5: Total amount of posts and users for each country in the dataset as well as number of posts able to be located and used.

7 Limitations

The overall sample size of reactions analyzed for the disclosure posts is very small. For example, our dataset has only 5 comments for the users disclosing their mental health in Australia. Similarly, 4 for India, and 6 for Nigeria. The country with the highest number of responses are the United States and the United Kingdom, with 25 comments (see table 5). This scarcity in responses limits our findings to be based on these few posts. The prevalence of X (Twitter) and the number of followers users have in each country may impact the amount of support users get. For instance, only 3.6M people use X in South Africa compared to 111.3M in the United States [World Population Review 2024].

Like other categorizations of countries around the globe, grouping countries into Global North vs Global South is not a perfect grouping mechanism, and has received criticisms recently [Patrick and Huggins 2023]. However, with its criticisms the countries in these two regions still exhibit cultural differences [Braff and Nelson 2022]. For the long-term effect analysis, for posts made three months before and after the disclosure post, there's an uncontrolled factor which is the number of followers for users may increase in this six-month range, hence the increase in reactions can be due to the differences in the number of followers. In addition, users'

long-term posting behavior may be impacted by several other confounding factors such as the in-person support and treatments users received. Future work can look at the relationship between offline (in-person) and its impacts on users on users online support seeking and long-term posting behaviors.

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A Appendix

A.1 Volume of Pre and Post Disclosure Post

In this section we provide the figures for users’ posting behavior up to three months before and after making a genuine disclosure post. See Figure 3 for Australia, 4 for India, 5 for Nigeria, 6 for South Africa, 7 for Philippines, 8 for the UK, and 9 for the US.

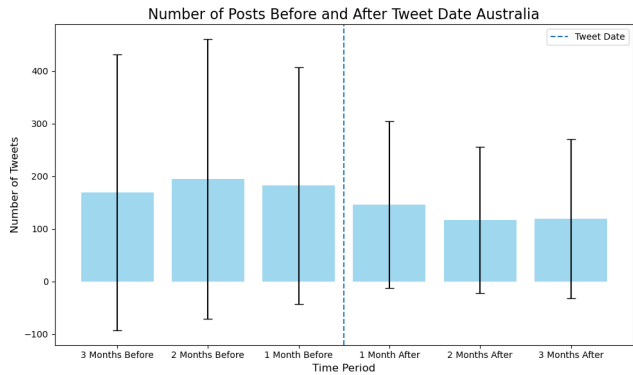


Figure 3: Number of posts made pre and post disclosure post in Australia

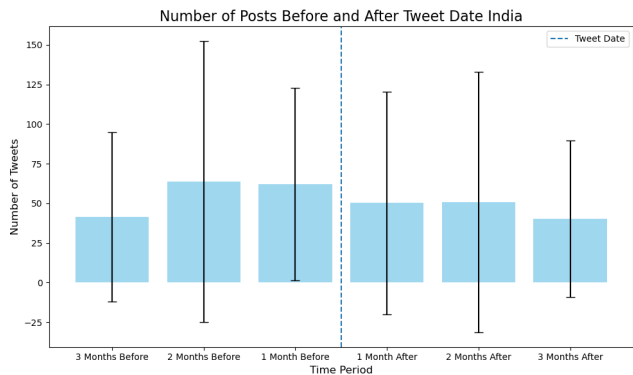


Figure 4: Number of posts made pre and post disclosure post in India

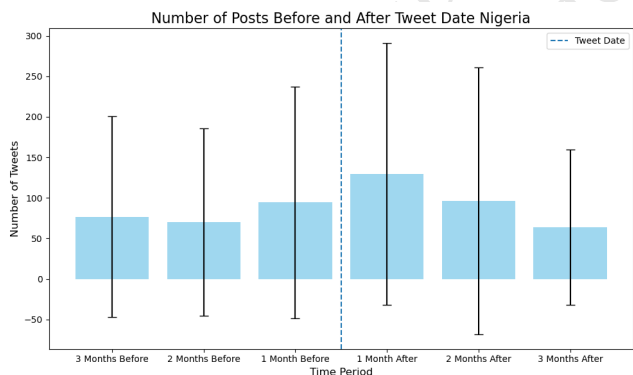


Figure 5: Number of posts made pre and post disclosure post in Nigeria

A.2 X (Twitter) User Distribution Across the Countries

The table 6 shows the distribution of X users for each country analyzed in our cross-cultural dataset. This shows South Africa has

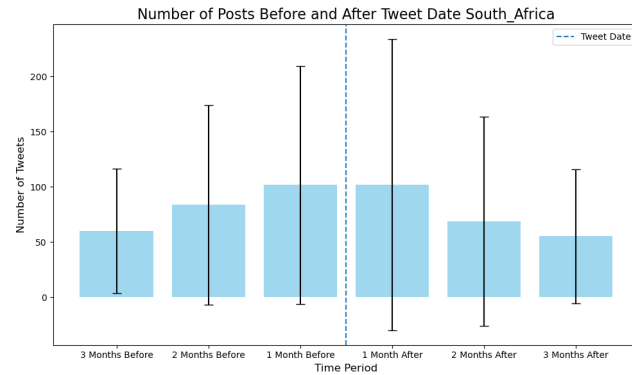


Figure 6: Number of posts made pre and post disclosure post in South Africa

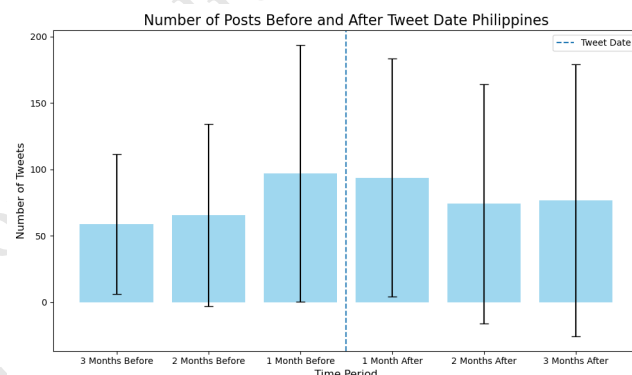


Figure 7: Number of posts made pre and post disclosure post in Philippines

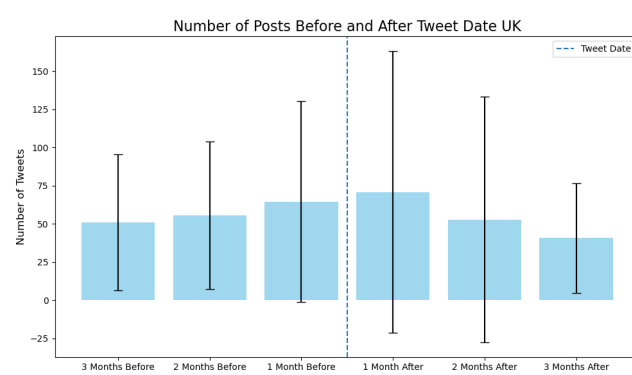


Figure 8: Number of posts made pre and post disclosure post in UK

the least number of X users (3.6M), followed by Australia (5.4M), whereas the majority of the users are in the United States (111.3M). This gives a perspective on X's prevalence in these countries and how it may be used for mental health support.

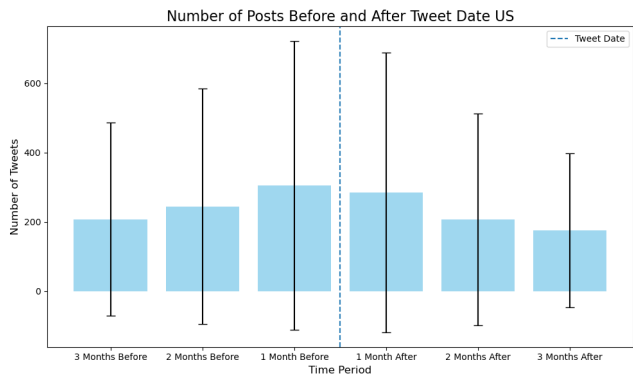


Figure 9: Number of posts made pre and post disclosure post in US

Country	Number of users
Australia	5.4 M
India	27.3 M
Nigeria	8.4 M
Philippines	11.1 M
South Africa	3.6 M
UK	25.9 M
US	111.3 M

Table 6: Total number X users per country according to a report from [World Population Review 2024] in 2024.

A.3 Post Engagement

Tables 7 and 8 give the percentage of posts with at least one or more comments, retweets, quotes, or likes. Table 7 shows that many users receive no reaction at all to their disclosure posts which means they are receiving no support. The reactions generally decrease from the non-disclosure set to the disclosure set which could be a result of social stigma.

A.4 Sample of Responses

This section presents examples of positive and negative comments in response to genuine mental health disclosures. For sets lacking sufficient negative reactions due to limited data, neutral responses are displayed instead. Notably, even comments classified with negative sentiment may not be inherently negative in intent, though such reactions could potentially have adverse effects on users who are disclosing their mental health struggles.

Australia

- Positive reaction: *[Four green heart emojis] a true king !*
- Negative reaction: *That’s awful. I’m sorry that you’ve been through that. Any suicide attempts are terrible,&I think that it makes the need for thorough talking therapies more apparent, to ensure underlying issues are resolved. Suicide rates for trans ppl are no lower for those who’ve transitioned.*

	Dataset	Reply	Retweet	Quote	Like
Country	Australia	13.79%	6.90%	0%	37.93%
	India	26.67%	13.33%	0%	13.33%
	Nigeria	26.67%	20%	0%	46.67%
	South Africa	34.48%	13.79%	0%	44.83%
	Philippines	33.33%	2.38%	0%	40.47%
	UK	43.90%	12.19%	4.88%	53.66%
	US	17.31%	15.38%	4.81%	43.27%
Global	MTL-D	19.81%	9.74%	0.06%	21.40%

Table 7: Percentage of posts with one or more comments, retweets, quotes, or likes in disclosure set.

	Dataset	Reply	Retweet	Quote	Like
Country	Australia	21.78%	14.34%	3.19%	48.07%
	India	12.92%	14.67%	2.87%	35.89%
	Nigeria	20.46%	12.34%	6.63%	33.03%
	South Africa	19.24%	11.07%	7.35%	29.81%
	Philippines	11.92%	10.03%	2.45%	32.38%
	UK	21.86%	10.05%	2.19%	41.82%
	US	25.44%	10.62%	3.19%	51.19%
Global	MTL-D	16.62%	8.90%	3.31%	24.98%

Table 8: Percentage of posts with one or more comments, retweets, quotes, or likes in non-disclosure set.

	Dataset	Reply	Retweet	Quote	Like
Country	Australia	5	2	0	39
	India	4	2	0	6
	Nigeria	6	2	0	6
	South Africa	12	5	0	23
	Philippines	10	1	0	30
	UK	25	23	2	315
	US	25	91	18	716
Global	MTL-D	932	930	2	2,457

Table 9: Total number of replies, retweets, quotes, and likes for the disclosure set

India

- Positive reaction: *Okay. Thanks. May the force be with you.*
- Negative reaction: *whyyy??*

Nigeria

- Positive reaction: *Don't be depressed my dear... Everything will be ok..*
- Neutral reaction: *We suppose yarn o*

Philippines

- Positive reaction: *Praying for you Gellia. God's joy comes on the morning. Rest well, tomorrow you will face a brand new day, brand new start. God bless! [Sun emoji]*
- Neutral reaction: *Why?*

South Africa

- Positive reaction: *I'm glad people like you are here to tell it like it is*
- Negative reaction: *Advise him that in this app no one is real and normal person can't get mad because people don't like his post. He have to much time in his life to worry about useless*

things. He was living before he join Twitter and now what changed. People are crazy over so called attention.

United Kingdom

- Positive reaction: *Tomorrow I promise to share this story with you, and how my puppy helped save my life. #mhaw17*
- Negative reaction: *Without the Sanaritans many more would be dead as there is zero help from the NHS.*

United States

- Positive reaction: *Omg this is a genius idea. Like please make me food or remind me to drink water or wash the growing pile of laundry that's been untouched for weeks.*
- Negative reaction: *That is true. It frustrates me*

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