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Denouncing Sexual Violence: A Cross-Language and Cross-Cultural Analysis of #MeToo and #BalanceTonPorc

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Abstract. #MeToo, a social media movement that denounced sexual violence against women was lauded as a global phenomenon. In this paper, we present a cross-language and cross-cultural quantitative examination of the English #MeToo and French #BalanceTonPorc. The goal of our study was to examine the global to local adoption and personalization of this social media movement. In part one of our study, we sought to understand linguistic differences by comparing #MeToo tweets in English and #BalanceTonPorc tweets in French. In the second part, we sought to understand cultural differences in the way #MeToo was adopted in the US and India. We found that the movement did not share a unified perspective, instead it was shaped by the culture and social reality of the posters; tweets in French were more aggressive and accusing than those in English, while English tweets from India involved more religion and society than those from the US.

Keywords: Twitter Trends · Linguistic Analysis · Social Movements

1 Introduction

Globally, one in three women is affected by sexual violence in her lifetime [26]. Sexual violence is defined as “any sexual act or an attempt to obtain a sexual act, unwanted sexual comments, or advances, acts to traffic or otherwise directed, against a person’s sexuality using coercion, by any person regardless of their relationship to the victim in any setting, including but not limited to home and work” [17]. Survivors of sexual violence have historically remained silent [1], yet in 2017 a global movement denouncing sexual violence unfolded across traditional [23, 4, 21, 38] and social media [32], which is perhaps most recognized in the form of #MeToo.

Though sexual violence is a gendered-and-cultural phenomenon [17], #MeToo was utilized in various countries to express facts, beliefs, and stories related to sexual violence on social media [16, 2]. While #MeToo was used at a global level,

various language-specific hashtags were used for the same purpose including but not limited to the Spanish #YoTambien (MeToo), the Italian #QuellaVoltaChe (TheTimeThat), and the French #BalanceTonPorc (DenounceYourPig). While some attention has been paid to the variants of the #MeToo movement [25, 11], there has not yet been an empirical study that compares linguistic attributes across the dimensions of language, culture, and place.

Our study analyzes two aspects of the global social media movement denouncing sexual violence. First, we present a cross-language, quantitative examination of the English #MeToo and French #BalanceTonPorc from a data set of 412,582 publicly shared tweets in 2017. Our findings reveal that users of each language participate distinctly, which bears implications for understanding global social media movements that are multilingual. Second, we present an analysis of over a million #MeToo tweets from 2018, written in English, from the US and India. This allows an investigation of cultural differences which affect expression in the same language in a social media movement.

Our research contributes to understanding of global social media movements across language, culture, and place. We examine how this phenomenon takes form for each and characterize user participation across linguistic dimensions, in order to highlight the differences in the movement and how different societies face a global issue.

2 Related Work

Social movements and collective action have been studied extensively within the social computing community [8, 13, 19, 22, 35]. Many of these studies have focused on social media movements at the local and national level [9]. However, research has noted that globalization and increased adoption of global communication networks (e.g. Twitter) has shifted the focus of social movements from local or national scale to a global scale [7]. Trans-nationally, members of social networks have advocated for specific causes and goals united through hashtag activism [36] such as Latin America’s #NiUnaMenos movement against femicide and gender-based violence. Despite global activism, pluralism of participation exists, and social media movements cannot be detached from underlying influences such as people, events [24], language, culture, and digital media platforms which influence the personalization of collective action [5]. Researchers have also investigated how Twitter reflects the views and perspective of users in India. For example, [30, 18] addressed the role that Twitter plays in understanding public health issues, finding similarities and differences between English Twitter users from the US and India. For example, when both groups tweeted about AIDS they focused on disseminating information about prevention and testing, but users from India were less likely to tweet about AIDS or autism and more likely to tweet about tobacco cessation than their US counterparts.

Framing theory, provides yet another way to think about social media movements. It is a concept from mass communication literature, that refers to the process by which media can be manipulated to highlight certain aspects of an issue

to orient an individuals thinking and perception around it [14]. Each frame includes a message, audience, participants, platform, context, and high-level moral and conceptual messages. Furthermore, Lakoff [20] states that these “frames” are evoked by language, and therefore the choice and structure of language is critical in frame theory. As mentioned previously, language is an important social lens, and discourse studies can inform socio-historical understanding of meaning as a product of a social group [3]. This makes analyzing tweets on sexual violence among different language communities an important endeavor. One question that should be answered in order to better understand the relationship between the people that speak the language and their cultural values is: *How do people relate the social context to the linguistic system?* In other words, *how do they frame their meaning via semantic exchange?* [20, 14]. This question is equally compelling when one considers a shared language in two very different cultures.

To our knowledge, little research has examined this global to local adoption and personalization of social media movements across language and culture in the social computing community. One notable effort in this space was conducted in the examination of the use of English and Arabic tweets during the 2011 Arab Spring [6]. Similarly, our study will adopt a view of the #MeToo movement through the language spheres of English and French. However, rather than focusing on information flow between spheres, we will examine how speakers of each language participated in the #MeToo social media movement concurrently and distinctly. We will investigate unique participation of US #MeToo and French #BalanceTonPorc tweets across language. We will also examine how culture affects the linguistic content of tweets written in English by people from India and the USA.

3 Data

In order to analyze the differences between content in French and English, we gathered a total of 4 datasets. For each language, we gathered tweets related to the global social media phenomena in which users shared content related to sexual violence. As is common, we also compiled control data sets with which we could compare tweets [10]. For the cultural analysis we retrieved 2 data sets, formed by tweets in English which could be attributed to users from the USA or India. In this section, we describe the methods used for acquiring this data.

The first part of our study uses 412,582 publicly shared tweets utilizing the hashtags #MeToo, #MoiAussi, and #BalanceTonPorc shared between October 13, 2017 and November 11, 2017. We collected data using both Twitter API via Tweepy [34] and the Github Library Taspinar¹. We used each of the hashtags listed and then concatenated our results, dropping duplicates based on the ID associated with the tweets. Tweets collected with the Taspinar Library did not have information about the user or language, however, we were able to use the tweet ID and Twitter API to complete the data set. We then created columns for

¹ <https://github.com/taspinar/twitterscraper> (2017)

hashtags (#), mentions (@), and URLs using a Regex Library. Next we applied a cleaning function which removed all punctuation, numbers, and set all text to lowercase. Finally, we divided the data set by language (English or French) in order to obtain two distinct, language-based data sets.

In order to provide a consistent cross-linguistic analysis, we developed a control data set for both English and French [10]. This comparison allows us to show that differences in tweets is influenced by the social media movement rather than language structure. Queries seeking a “random” set of tweets are not permitted via the Twitter API. Therefore, in order to create our control data set, we collected tweets from the same time period which mentioned common topics. In order to collect tweets on these topics we first collected tweets with the most used French and English words ($q = \text{the, it, I, this, a, les, le, jai, cest}$). We then sourced tweets regarding sports ($q = \text{NFL, Ligue1}$), television shows ($q = \text{The Voice}$), and tweets related to commercials ($q = \text{contest, concours}$).

For the second part of our study we used the official Twitter API through the Tweepy library to gather metadata. We retrieved over 2 million tweets which used the hashtag #MeToo and were shared between October 9, 2018 and November 25, 2018; next we used a language detection library to discard those tweets that were not written in English. We then classified the tweets as coming from either “India”, “USA” or “Other”, discarding the latter. This reduced the number of tweets to 1,511,161; these tweets were divided in two data sets based on country of origin.

The classification of tweets by country was done using the following data when available: 1) the coordinates of the tweet, 2) the coordinates of the bounding box associated with the user who shared the tweet, 3) the location of the user as published in their profile. If the tweet was actually a retweet the information from the original poster was used. If none of this data was available or if the tweet was matched to a country different from the USA or India it was classified as “Other” to be discarded.

4 Methods

To quantify cross language dimensions in our datasets, we define 3 categories of linguistic measures: **(1) affective attributes** marked by words related to emotion as well as the polarity of the emotions expressed, **(2) cognitive attributes** which relate to sensory information, and **(3) linguistic style attributes** related to the use of pronouns and common nouns. To evaluate these measures we use LIWC [27] a well known and validated linguistic analysis tool [15, 37]. Previous work in this area identifies this tool and its categories to be valuable in evaluating the linguistic differences on social media for a variety of purposes [31, 9, 15]. We use two LIWC dictionaries appropriate to the dataset languages. For French, we used Piolat’s [29] which corresponds to LIWC 2007. Although an updated version of the official English dictionary exists [28], in order to maintain equivalency between the dictionaries we used the LIWC 2007 as well.

5 Results

Content Discrepancies between Languages In our data, we observe that 52% of English tweets contain an external link whereas only 36% of French tweets do in comparison to our control data sets for both languages. These findings make sense if we consider that sharing URLs is in line with the goal of promoting awareness about sexual violence; which is the objective of the #MeToo movement. In the 2018 data sets, the tweets from the USA were also more likely to include URLs which might indicate that it is a tendency which has more to do with the country than the language itself.

Linguistic Differences We observed many significant statistical differences between the French and English data sets on Table 1 and between the India and USA data sets in Table 2. To identify the significant results we looked at the average differences as well as the differences between the Z-score statistics. (See Tables 1 and 2 for details). We also replaced the p values under 0.0001 with 0.

A Negatively Charged Social Media Movement #MeToo and #BalanceTonPorc tweets are charged with negative emotions such as anger as one might expect with talk of sexual violence. When compared to our control data set, there is approximately a 50% difference in negative tone of tweet when compared to tweets outside the movement. French tweets have less affect (the emotional charge based on the number of words related to feelings) than English ones and use more aggressive, vulgar language. This difference may be explained by the tone of each social media campaign. #MeToo suggests solidarity whereas #BalanceTonPorc encourages women to “out your pig,” as illustrated below:

#MeToo has been a mix of emotions. I am sharing my story...

Translation: [Expletive] patriarchy!

In #MeToo tweets from 2018 we observed that tweets from the USA had less affect than tweets from India, meaning that they expressed fewer emotions. This could be due to the fact that the movement in India is just getting started and there are many tweets denouncing abuse.

Cognitive Attributes: Creating Solidarity or Denouncing Perpetrators The goal of #MeToo was to create a survivor to survivor network whereas #BalanceTonPorc was to identify and denounce perpetrators of sexual violence. Our analyses show that denouncing individuals is much less likely in the English than the French data set, as seen below:

#MeToo is inclusive because of our shared words and experiences among women- that is the whole point.

Translation: Agh! Indeed, I think we will have a special category for the white males who do not like this hashtag!

Furthermore, tweets from the French data set were more likely to describe the appearance of the perpetrator along with their own feelings about the encounter.

Table 1. 2017 Dataset: LIWC Cross-Language Results, Z statistics calculated with a Wilcoxon Rank Sum test and the size effect with Cohens indicator

	$\mu (FR_C)$	$\mu (EN_C)$	Z_C	$\mu (FR)$	$\mu (EN)$	Z_{2017}	P_{2017}	d_{2017}
Affective Attributes								
Affect (emotion)	7.774	7.035	16.88	5.167	6.749	-41.83	0	-0.188
Posemo	6.436	5.126	43.35	2.631	3.303	-16.01	0	-0.103
Negemo	1.301	1.88	-78.92	2.705	3.417	-23.98	0	-0.122
Anger	0.477	0.846	-55.5	1.122	2.302	-49.9	0	-0.261
Swear	0.208	0.396	-28.31	0.303	0.212	7.3	0	0.048
Cognitive Attributes								
Hear	0.447	0.649	-38.15	0.794	1.104	-9.89	0	-0.096
See	0.961	0.992	-21.85	0.785	0.501	16.94	0	0.117
Feel	0.43	0.447	-9.18	0.539	0.346	11.4	0	0.097
Linguistic Style Attributes								
Interpersonal Focus								
I	2.603	4.565	-209.6	2.933	2.799	13.29	0	0.023
We	0.358	0.599	-39.41	0.293	1.14	-32.77	0	-0.192
She/He	3.654	0.811	264.2	4.268	0.768	143.4	0	0.895
They	0.267	0.462	-36.25	0.448	0.485	-5.65	0	-0.017
Social Personal Concerns								
Family	0.223	0.237	-6.93	0.953	0.265	41.79	0	0.322
Friend	0.289	0.194	9.57	0.257	0.127	9.22	0	0.106
Social	3.718	7.67	-283.4	4.558	11.129	-142.8	0	-0.619
Health	0.506	0.493	0.49	0.602	0.385	13.54	0	0.1
Body	0.536	0.637	-26.46	1.304	0.375	48.53	0	0.371
Relig	0.18	0.274	-16.96	0.209	0.281	-3.45	0.001	-0.032
Sexual	0.276	0.553	-39.7	1.292	1.632	-15.57	0	-0.091

Translation: That guy...with a very unhealthy and insistent stare.

Tweets from India were also much more likely to denounce an individual than tweets from the US, but they were less likely to give a clear description of an attack.

Linguistic Style Attributes: Use of Pronouns There are notable differences between the use of pronouns in the social media movements of #MeToo and #BalanceTonPorc. The measure of the English I and French j or j show that French tweets utilize the first person more often. English tweets utilize “we” 90% more than in the French data set.

#MeToo is here to stay! We must challenge sexual harassment!

When comparing India and the USA, personal pronouns are used more often with the exception of the third person plural “they”. The latter is used more frequently in tweets from India, where the focus seems to be placed on men as a group and in society in general.

Men in the social sector are equally oppressive and abusive. They hide behind the cloak of 'wokeness' and understanding consent...

Table 2. 2018 Dataset: LIWC Cross-Language Results, Z statistics calculated with a Wilcoxon Rank Sum test and the size effect with Cohens indicator

	μ (USA)	μ (India)	Z ₂₀₁₈	P ₂₀₁₈	d ₂₀₁₈
Affective Attributes					
Affect (emotion)	5.402	5.74	-43.39	0	-0.072
Posemo	2.467	2.545	-20.75	0	-0.023
Negemo	2.914	3.152	-41.33	0	-0.067
Anger	1.967	1.874	35.46	0	0.033
Swear	0.103	0.059	11.23	0	0.069
Cognitive Attributes					
Hear	0.848	0.874	-4.35	0	-0.015
See	0.603	0.37	62.13	0	0.162
Feel	0.288	0.193	55.68	0	0.105
Linguistic Style Attributes					
Interpersonal Focus					
I	1.814	1.43	45.77	0	0.119
We	0.694	0.457	75.07	0	0.155
She/He	1.531	1.483	7.06	0	0.017
They	0.506	0.542	-13.87	0	-0.024
Social Personal Concerns					
Family	0.326	0.39	17.52	0	-0.049
Friend	0.102	0.132	-4.68	0	-0.045
Social	9.158	9.221	-3.29	0.001	-0.009
Health	0.236	0.226	-4.16	0	0.01
Body	0.253	0.307	-25.69	0	-0.051
Relig	0.244	0.781	-98.45	0	-0.277
Sexual	1.152	0.987	48.74	0	0.08

Use of Words Related to Family Ties

Both French and English tweets use words related to family (e.g. father, uncle). However, these were much more present in the French data set, often denouncing family members who were involved in perpetrating sexual violence. This is not surprising considering approximately 30% of child sex offenders are family members [33]. Rather than naming or tagging these perpetrators, French tweets identified the familial relationship.

Translation: My uncle who abused me, from when I was X to X years old...

Description of Assault

The French tweets more often described details and characteristics of the sexual violence than did English tweets.

Translation: This guy who puts his hand on my bottom...

When compared to the US, tweets from India are much more often related with religion and contain more references to body parts, although the language used is less explicit as reflected in the lower score on the “sexual” category.

6 Discussion

In 2017, #MeToo, a social media movement that denounced sexual violence against women was lauded as a global phenomenon [23, 4, 21, 38, 32]. In this paper, we presented a cross-language and cultural based quantitative examination of the English #MeToo and French #BalanceTonPorc. The goal of our study was to examine the global to local adoption and personalization of this social media movement. We sought to understand linguistic and cultural differences between the US and France and the US and India, respectively.

We found that the global movement did not share a unified perspective. Tweets from the US, France, and India all demonstrated semantics which indicate a unique, local social perspective. It was not the case that there was a global #MeToo that denounced sexual violence but rather that two linguistic and two cultural communities found their own voice. We believe that this likely stems from the initial framing set out in the US [12] which called for solidarity and support; whereas in French [11] the call was to share experiences and identify the perpetrators. It could also be argued that these distinctive frames [20, 14] oriented participant’s thinking about how to respond to these first tweets. Thus, as the volume of tweets increased, our evidence shows that these frames were reinforced throughout the data sets for each language.

When comparing English #MeToo and French #BalanceTonPorc tweets we found that the latter were more likely to include words that indicated that there was a narrative rather than simply raising awareness. We found that compared to English, French tweets were more likely to be in the first person, more likely to include body terms and number words. Further, they were more likely to include male family terms. The French tweets were also found to have a more negative emotional valence and vulgar words. All this underscores the fact that French women were more likely to include their personal story about how old they were and what happened to them. This shows that the 2017 datasets were able to prove that the differences between the #MeToo and #BalanceTonPorc tweets were not only due to different languages but to the fact that the French movement focused on denouncing attacks.

When we look at #MeToo from a cultural versus a linguistic lens a different narrative appears. Here we see that shared language does not reflect a shared expression. Tweets from each country posted content which adjusted to the needs and customs of their societies. Indian tweets were more likely to refer to religious themes, shared less explicit content, and had a bigger focus on denouncing society and men as a group.

In conclusion, our analysis is in line with other findings that microblogs such as Twitter can shed light on contemporary events. Despite some limitations, our findings open up new avenues of research in the area of social computing.

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