The Refugee/Migrant Crisis Dichotomy on Twitter: A Network and Sentiment Perspective

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ABSTRACT

Media reports, political statements, and social media debates on the refugee/migrant crisis shape the ways in which people and societies respond to those displaced people arriving at their borders world wide. These current events are framed and experienced as a crisis, entering the media, capturing worldwide political attention, and producing diverse and contradictory discourses and responses. The labels "migrant" and "refugee" are frequently distinguished and conflated in traditional as well as social media when describing the same groups of people. In this paper, we focus on the simultaneous struggle over meaning, legitimization, and power in representations of the refugee crisis, through the specific lens of Twitter. The 369,485 tweets analyzed in this paper cover two days after a picture of Alan Kurdi – a three-year-old Syrian boy who drowned in the Mediterranean Sea while trying to reach Europe with his family – made global headlines and sparked wide media engagement. More specifically, we investigate the existence of the dichotomy between the "deserving" refugee versus the "undeserving" migrant, as well as the relationship between sentiment expressed in tweets, their influence, and the popularity of Twitter users involved in this dichotomous characterization of the crisis. Our results show that the Twitter debate was predominantly focused on refugee related hashtags and that those tweets containing such hashtags were more positive in tone. Furthermore, we find that popular Twitter users as well as popular tweets are characterized by less emotional intensity and slightly less positivity in the debate, contrary to prior expectations. Co-occurrence networks expose the structure underlying hashtag usage and reveal a refugee-centric core of meaning, yet divergent goals of some prominent users. As social media become increasingly prominent venues for debate over a crisis, how and why people express their opinions offer valuable insights into the nature and direction of these debates.

KEYWORDS

Refugee Crisis; Twitter; Network Analysis; Sentiment Analysis

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1 INTRODUCTION

Media reports, political statements, and popular discourse on the refugee crisis shape the ways in which people and societies respond to those arriving at their borders. These current events are framed and experienced as a crisis, entering the media, capturing worldwide political attention, and producing diverse and contradictory discourses and responses.

The labels "migrant" and "refugee" are frequently distinguished and conflated in media, political, and popular discourse when describing the same groups of people. Such labelings do not only create a demarcation between the refugee versus the migrant, but also point towards the causes of displacement – specifically those related to the overlapping dichotomies of voluntary/forced, (im)migrant or refugee, and economic/political. These types of dichotomies have shaped how states and other actors have responded to displaced people [15, 19, 43].

International conventions establish refugees as involuntarily displaced by political circumstances, including war and violence, and natural disasters; refugees are thus framed as "deserving". On the other hand, immigrants or migrants are portrayed as economic opportunists, voluntarily leaving their home communities in search of a better life, and hence become viewed as "undeserving" of understanding or sympathy. The use of such dichotomies has the potential to shape the story on migration, and the ways in which we perceive migrants and refugees. Labeling these displaced people as either refugees or migrants in communication contexts may affect receivers by emphasizing different frames for the evaluation of the same issue or event [e.g., 7, 10, 11, 14, 33].

Through framing, certain features of an event are selected while others are excluded [23], and frames may shape one's interpretation of that story by making certain perspectives more salient [16, 23, 29]. Drawing from the work of Goffman [14], we understand that frames elicit, as well as constrain, the interpretative activities of audiences [29]. Entman [11] defines framing as a way "...to select some aspects of a perceived reality and make them more salient in a communicating text, in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation." By highlighting certain characteristics of an issue and concealing others, framing reflects the emphasis of the author.

Without trying to reduce the crisis to mere text or discourse, we seek to analyze representations of displaced people in popular discourse as well as the increasingly evident demarcation between the "deserving" *refugee* versus the "undeserving" *migrant*. As previous research has shown, such dichotomized characterizations strongly relate to sentiment towards the refugees and the crisis itself [20, 25], while framing both groups as outsiders threatening the well-being of the host societies. This discourse of deservingness shifts blame and responsibility away from political and economic actors, placing it instead onto the displaced people themselves. Furthermore, such dichotomized categorizations together with media representations of Syrian refugees – as connected to the violent November 2015 attacks in Paris [1], refugee centers being set on fire in several European countries (e.g., Germany, Sweden etc.), politicians being violently attacked for supporting refugees [21], and boats of refugees being turned back to sea [24] – build what [Feitlowitz] refers to as a "lexicon of terror."

In this paper, we focus on the simultaneous struggle over meaning, legitimization, and power in representations of the refugee crisis, through the lens of social media, through which the refugee crisis has received much attention. In particular, Twitter users have been increasingly vocal in their opinions of the crisis ever since the reporting of the death of Alan Kurdi on September 4, 2015.

Twitter debates expose public-opinion-based characterizations of global events [31], such as the refugee/migrant crisis, while also revealing opinion communities and their interactions (i.e., through mentions of other users and following/follower relationships) [17]. To uncover patterns of opinion and influence, meaning structures as well as social interactions related to the refugee crisis debates on Twitter, we employ a suite of analysis methods, including the increasingly popular socio-semantic framework [3, 9, 17, 35–37].

2 AIMS AND HYPOTHESES

The main aims of this paper are to investigate the existence of the dichotomy between the "deserving" refugee versus the "undeserving" migrant (discussed above) in the refugee crisis debates on Twitter, as well as to explore the relationship between sentiment expressed in tweets, their influence, and the popularity of Twitter users. Based on these aims we formulate a number of hypotheses:

> **H1:** Tweets employing hashtags containing the word refugee will be more positive in sentiment, while those employing hashtags containing the word migrant will be more negative in sentiment.

The sentiments of tweets themselves have influential impacts, that may be heightened by the popularity of the tweet poster (i.e. 'tweeter' or user) or the tweet itself. For example, the top one percent of social media authors have been found to significantly influence the whole sentiment of a topic [34]. Popularity confers not only readership but influence as well. That is, the sentiments expressed by popular users in their tweets have been found to influence the sentiment of their audience [2]. The outcomes of such influential forces can be broad reaching. For example, many studies have linked sentiments on Twitter as predictors of elections [8, 27, 41]. Along those lines, we first consider the sentiment quality of popular Twitter users and hypothesize that intense expression is likely to garner more attention, and those Twitter users who are the center of attention may express themselves with more intense rhetoric:

> **H2:** The popularity of Twitter users is strongly related to the average sentiment intensity of their tweets.

Retweeting, an indicator of the influence of a tweet, can be driven, in part, by a tweet's sentiment. For example, sentiment occurring in politically relevant tweets has been found to have an effect on their re-tweetability (i.e., how often these tweets will be retweeted) [38]. In fact, it has been observed that tweets with positive sentiment polarity spread 15-20 percent more than tweets containing negative sentiment polarity [6]. Here, we hypothesize that incendiary or otherwise sentiment-laden tweets will be more influential:

> **H3** The influence of a tweet is directly related to the sentiment intensity of the tweet.
> **H4** Positive tweets are retweeted more often than negative tweets.

3 DATA AND METHODS

We analyze a total of 369,485 historical tweets collected using the ten most popular and relevant Twitter hashtags surrounding the refugee/migrant crisis.[1] This data set was obtained from historical Twitter data providers Gnip/Sifter and constitute 100% of the available tweets within our search criteria and searched dates (similar to the Twitter Firehouse). The data spans two full days, between September 4, 2015 – when the death of Alan Kurdi sparked wide social media engagement to the crisis – and September 5, 2015.

In analyzing this data set, we employ sentiment analysis, regression analysis, and network analysis. In the following sub-sections, we elaborate on each of these methods.

3.1 Network analysis

In recent decades, network analysis has gained popularity across the social sciences, yielding explanations for a wide variety of social phenomena [5]. Network analysis methods investigate social phenomena through the use of network structures and graph theory, and they characterize networked structures in terms of nodes (e.g., individual actors) and the links (relationships or interactions) that connect them [42].

In this paper, we make use of network analysis methods to uncover interconnections between users and tweet contents, and thus co-addressing both meanings and actors surrounding the refugee crisis debate on Twitter. To this end, we investigate two types of networks: 1) the network of hashtags and 2) the socio-semantic network of users and their used hashtags. While the first type of network comprises nodes of a single type (i.e., hashtags) and hence is unimodal, the second type of network is called bimodal.

Bimodal networks (also known as affiliation, bipartite, or two-mode networks) contain two different sets of nodes, distinguished by qualitative, nominal categories. These networks link nodes belonging to different sets [4, 26, 28]. In the specific case of our user-to-hashtag network, the two types of nodes represent Twitter users and the hashtags they employed. This specific network helps us explore the relationships between users through the shared usage of relevant hashtags, which serve as proxies for larger topics.

Furthermore, both types of networks analyzed in this paper are co-occurrence networks and hence the value of strength for each link in these networks is determined by the frequency of

[1]The following hashtags have been used when collecting our data: #migrantcrisis, #migrants, #migrant, #refugee, #refugees, #refugeecrisis, #syrianrefugees, #syrianrefugeesgr, #refugeeswelcome, and #muslimrefugees.

co-occurrence [42]. In other words, we do not only account for the existence of the the connection between co-occurring hashtags within each tweet or co-occurring users and hashtags, but also for the frequencies of these co-occurrences. For example, if #RefugeesWelcome and #Syria are observed together in exactly 100 tweets, then the link weight between these two hashtags would be the weight of 100.

For the purpose of this paper, we explore single snap-shots of these two types of networks via visualizations and also by measuring and reporting the weighted degree centrality of the network nodes. Degree centrality is one of the most commonly used centrality measures in social network analysis [18]. The degree centrality of a node in a network reflects the number of other nodes incident to the focal node [13] (or, in the case of weighted networks, the sum of the weights of all the incident links), and thus measures the involvement of a node in its local network. Nodes with low (weighted) degree centrality are potentially more peripheral to the network [22] unless they are connected to popular others. Thus, by calculating the weighted degree centrality of the nodes in our networks, we identify the most popular hashtags and the most central Twitter users, respectively. While some could argue that hashtag frequency, or the number of tweets a users has generated, are arguably more parsimonious metrics than popularity (i.e.,degree centrality), the network linkages (such structures surrounding connective hashtags and users) would remain obscured, resulting in a less accurate depiction of hashtag use.

In sum, through these two types of networks, we investigate several critical issues regarding the discussion of the refugee crisis on Twitter. Furthermore, we identify opinion leaders by their hashtag usage and structural positions, since networks, more than demographics, can characterize Twitter opinion leaders [30].

3.2 Sentiment Analysis

In order to explore the relationships between sentiment expressed in tweets, their influence, and the popularity of Twitter users, we use Thelwall's SentiStrength [40], which provides scores on two dimensions of sentiment (positivity and negativity) per emotional term and phrases within the tweet. In addition to the lexicon-based sentiment identification, SentiStrength also assigns sentiment to emoticons based on a list with human-assigned sentiment scores. SentiStrength employs a lexicon similar to LIWC (Linguistic Inquiry and Word Count) [32]. Sentiment scores from SentiStrength range from 0 to 4 for capturing the extent of the Positive and Negative sentiment dimensions in a segment of text (i.e., tweet). The initial SentiStrength scores of -1 to -5 for negativity and $+1$ to $+5$ for positivity were recoded into the 0-4 range, in which higher numbers indicate more intense sentiment, since -1 and $+1$ represent neutrality in the software. Thus, a tweet with a 0/0 score would be considered neutral, a tweet scored 4/0 would be considered extremely positive, while a tweet scored 0/-4 would be considered extremely negative.

Adding the two sentiment dimensions yields a sum score (we call 'Sentiment') capturing the overall sentiment of each tweet. Thus, a Sentiment score of $+1$ would indicate that the net sentiment of a tweet is slightly positive. Finally, an Intensity score — operationalized as the Euclidean distance of the sentiment score to (0,0), $\sqrt{\text{Pos.}^2 + \text{Neg.}^2}$ – captures the overall intensity of both sentiment valences together. As the term 'refugee' and its variants are detected as carrying negative sentiment (rescaled score of -1 in SentiStrength), they are omitted from the analysis, given our focus of analysis on the sentiment surrounding (and not including) the use of the terms refugee and migrant in hashtags. Incidentally, the term 'migrant' bears no such sentiment bias.

As the hypotheses relate Twitter user and tweet characteristics (metadata) to sentiment, we operationalize user popularity, influence of the user, and influence of the tweet. Popularity is expressed as the number of followers for each tweet's user. Influence, a score provided by Texifter [39], is the ratio of 'followers' to 'friends' (i.e., count of those whom the user follows). When the number of friends is 0, the Influence score is undefined; hence, we introduce a slight bias by adding 1 to the friends count, thereby capturing the influence of those without any friends (i.e. do not follow others).

However, given that the Influence score does not capture the impact of a tweet, we also include Retweets, the number of times each unique tweet has been retweeted. Retweets may appear multiple times in the data set, so we only account for highest retweet count of each retweeted tweet. Each of these metadata-based dependent variables has been transformed by $\log(x + 1)$ so that their distributions are less skewed and more Gaussian (i.e. normal).

3.3 Regression Analysis

Additionally, ordered logit (i.e., ordinal logistic) and OLS (ordinary least squares) regressions are used to predict key measures. For the integer sentiment measures (Positivity, Negativity, and Sentiment), the ordered logit is employed, while OLS is more appropriate for the sentiment Intensity measure. These sentiment measures are predicted by hashtag usage in order to test H1.

OLS regressions are also used to regress popularity, influence of the user, and influence of the tweet on sentiment measures, while controlling for the hashtags employed in order to test H2 and H3.[2] Popularity refers to the number of followers of the users, Influence refers to the influential position of the tweeter, while Retweets is simply the maximum number of times a unique tweet was retweeted by other users. The covariates of these regressions can be used to characterize the popularity, influence of user, and influence of the tweet.

4 RESULTS

4.1 Network Analysis

4.1.1 Hashtag Usage. In Figure 1, we show a hashtag co-occurrence network with the top 10 most central hashtags highlighted by revealing their labels. All hashtags in this network are colored by frequency of overall occurrence, ranging from blue for low frequency (minimum of 1) to red for high frequency (maximum of 18232). This frequency of occurrence refers to total usage of the hashtag, not dependent on co-occurring use with other hashtags. The nodes are sized by the total number of co-occurrence links to other hashtags (i.e., their weighted degree centrality). The links in the network are scaled by their weight (hashtags occurring together in tweets will have a stronger, and thus thicker, link).

[2] Specifically, we predict the logarithms of the dependent variable plus 1 to render their distributions and the residuals more normal while accounting for 0 values.

Table 1: Frequency counts for hashtag co-occurrence

Hashtag	Hashtag	Freq. of co-occurrence
hungary	refugee	18232
austria	refugee	9488
austria	hungary	8899
refugeeswelcome	refugeecrisis	8553
syria	refugee	7408
refugee	refugeeswelcome	6466
refugee	refugeecrisis	6116
refugeeswelcome	aylan	5403
refugee	budapest	5269
hungary	refugeecrisis	3922

Based on this portrayal, in Figure 1, we note that #refugee is by far the most frequent hashtag as well as the hashtag that is most frequently used in combination with other hashtags. Also, we note that migrant-related hashtags are very low in both frequency and centrality in our data set, indicating that they were not used as frequently as the refugee relate hashtags. In fact, only two migrant hashtags appear in the network.

Table 1 displays the top ten pairs of hashtags based on co-occurrence in tweets (link weights). These pairs of hashtag clearly contain those countries directly involved in the crisis back in September 2015. Many of the refugees fled conflict in Syria and entered Hungary, in large numbers, posing logistical and political difficulties. Austria, bordering Hungary, was similarly affected and demarcated refugees' transition further into Europe. Interestingly, the more positive hashtag #RefugeesWelcome is not associated with any of the country hashtags.

By all appearances, these findings seem to point towards the fact that the Twitter debate on the refugee crisis captured by our data sample has been predominantly focused on the refugee label, and not so much on the migrant labels. Based on the dichotomy we referred to earlier between the "deserving" refugee versus the "undeserving" migrant, a debate mostly focused on the refugee label may indicate a highly sympathetic tone towards those at the center of the debate – the displaced people fleeing zones of conflict. To further investigate whether the sentiments associated with refugee hashtags are indeed more positively laden, in Section 4.2 we perform sentiment analysis on tweets containing the two different types of hashtags, and on those tweets containing both types of hashtags.

4.1.2 Socio-Semantic Networks. For our socio-semantic network analysis, through which we explore both meanings and users within the Twitter refugee crisis debate, we present a snapshot of a bimodal user-to-hashtag network in Figure 2. In this network, Twitter users are linked to the hashtags they used in their tweets.

In Figure 2a, only nodes having a weighted degree centrality greater than or equal to 50 are displayed, in order to identify the more prolific actors and the most used hashtags. The center of the network is occupied by hashtags, the visible ones being the refugee-related ones appearing in Table 1, the most prominent of which is '#refugee' (frequency = 8474). The next two are #refugeeswelcome (5059) and refugeecrisis (4288). Surrounding this core are the users who employed those hashtags, while the periphery contains less prominently used hashtags. The most prominent user also lies in the periphery. However, this users' hashtag use, while sharing #refugee, appears to also employ lesser used hashtags that focus on women's issues in relation to the crisis: #refugee, #women, #womenshealthday, #girls, #displaced, #health.

In Figure 2b, we focus in on the top three most central users. The most central Twitter user in our data set is connected to the other two next most central users only through the common use of the #refugee hashtag.[3] By central, we refer to high weighted degree centrality (i.e., high hashtag usage) rather than a visually central position. Furthermore, by noting the width of the link connecting this highly central user to #refugee, we can easily note the frequent usage of this hashtag (more precisely 413 times).[4]

The central user is further distinguished by the visual distance between the user and its hashtags, indicating its hashtags are either not co-used by others, or used by others that employ very different hashtags. This heterogeneity of hashtag use by this user (with high level of use of each of those distinct hashtags) may indicate a singular focus not readily shared by other users. Hence, this lack of shared meaning with others renders this active user to be peripheral. Future analysis on tweets occurring after September 2015 will reveal whether or not this focus on women becomes shared by others or remains isolated.

While this central user focuses on topics unrelated to the other two central users, the latter two do share several common hashtags. Furthermore, these users exhibit greater variety of hashtag use, meaning their Twitter expression is more qualitatively central to the larger refugee/migrant discussion.

The bimodal socio-semantic depiction is particularly useful in this case, as it exposes the distinct position of the most central user, as being structurally and topically peripheral and, at that stage of the crisis, uninfluential and less embedded in the broader discussion. A unimodal network of users connected by co-use of hashtags (i.e., shared meanings) is more typical in network analysis; however, this depiction may be misleading by revealing this "central" user to be even further embedded than he or she actually is.

4.2 Sentiment Analysis

In Figure 3, we explore the sentiment distribution across tweets by partitioning them based on use of 'migrant'-related hashtags only (e.g., #migrantcrisis or #migrant), use of 'refugee'-related hashtags only (e.g., #refugeeswelcome or #refugeecrisis), and those containing both types of hashtags (see number of tweets for each type in Table 2). Each cell's percentage refers to the proportion of tweets for each type of hashtag use that are scored with a particular pair of positive and negative sentiment scores. The colors denote the balance of sentiment (sentiment sum): green for net positivity and red for net negativity.

While a good proportion of all three types of tweets are scored as purely neutral (upper left cell of Figure 3), their differences point to general sentiment variations. Migrant tweets (i.e., those tweets having only migrant-related hashtags) show the least neutrality,

[3]The #refugee and #refugees hashtags are merged to a singular #refugees node.
[4]For anonymity reasons, we choose not to reveal the usernames of the actors in our networks.

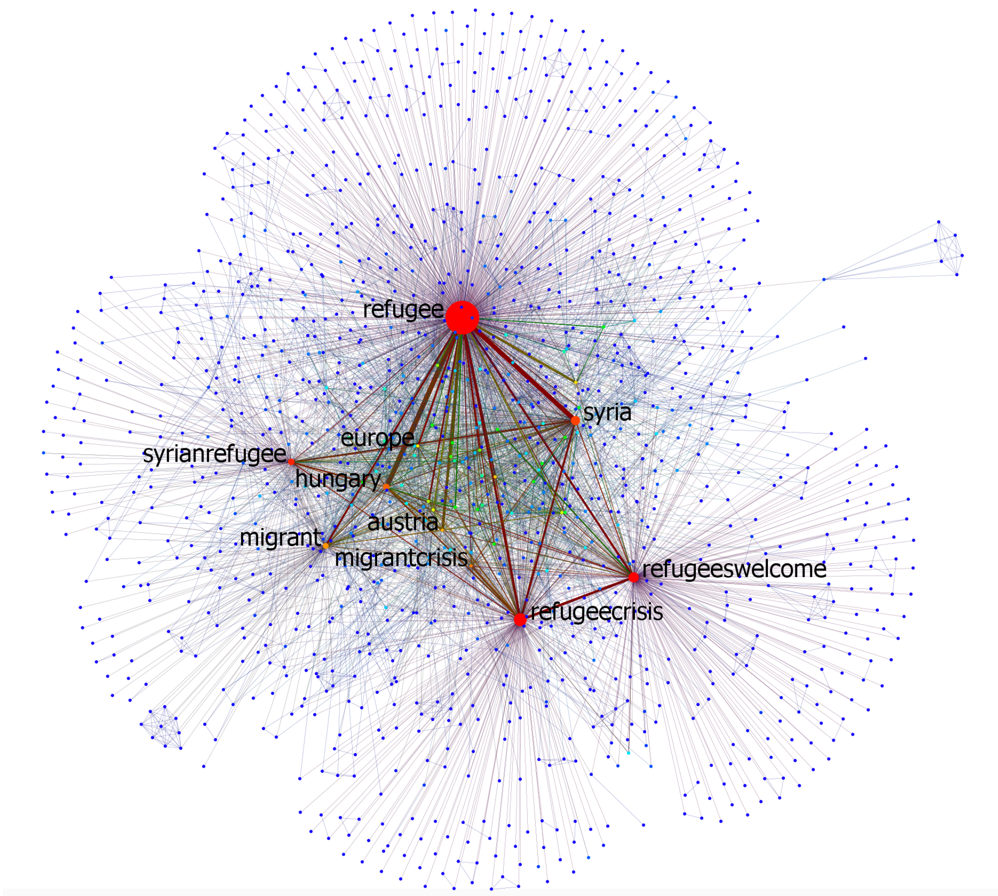


Figure 1: Hashtag co-occurence network ($N = 1335$, $E = 9508$); Nodes are sized by total degree centrality and colored by frequency; Link widths scaled by weight.

Table 2: Number of tweets using migrant, refugee or both hashtags

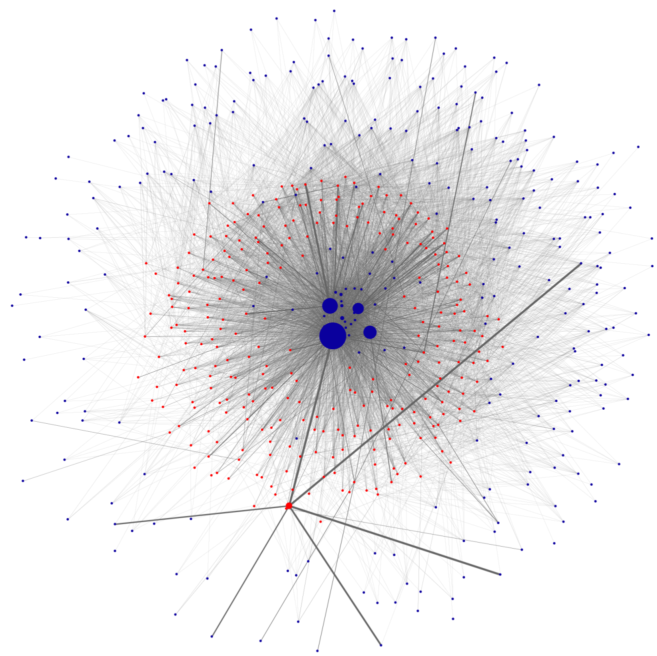
Type of tweet	Number of tweets
Migrant hashtags only	16,657
Refugee hashtags only	339,476
Both hashtags only	13,350

meaning higher levels of sentiment of some degree and valence. Refugee tweets bear the most neutrality, which is largely due to its incurring less negativity; the percentages in the distribution along the 1st column, where positive sentiment is 0, show overall less negativity for the non-neutral cells in Figure 3b. As argued earlier, the concept of refugee is likely to draw less controversy (i.e., negativity), which is evidenced in its sentiment distribution.

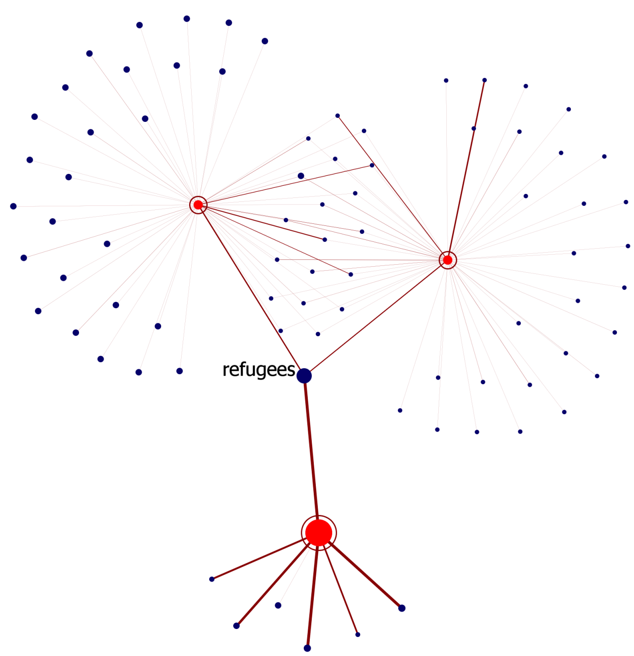
The distribution of tweets for joint hashtag use reflects the mixture of sentiment incurred by the more negative migrant discussion and the more positive refugee discussion. Interestingly, the $(+2, 0)$ cell deviates noticeably from this pattern. A greater proportion of mixed refugee-migrant hashtag tweets harbor moderate positivity, potentially attesting to some level of recognition and sympathy to the refugee-migrant dichotomy.

In regression models of Table 3, the extent of hashtag usage impacting Positivity, Negativity, overall Sentiment, and sentiment Intensity are reported. Negativity has been rescaled to 0–4, with higher values indicating more negativity in a tweet. The Constant here refers to when both types of hashtags are used in the same tweet.

We find that tweets employing only refugee hashtags are significantly more positive and less negative than those tweets using both refugee and migrant hashtags. Naturally, the overall Sentiment of the refugee-only tweets are more significantly positive than the other two types of hashtag use. Further, those using only migrant hashtags are also significantly more negative than either types of hashtag use, although it is only slightly more negative than those tweets with both types of hashtags. These observations confer less Intensity in refugee-only related tweets and slightly more (due to higher negativity) in migrant-only related tweets. Thus, we confirm higher antipathy towards the "undeserving" migrants and/or greater sympathy towards the "deserving" refugee, as proposed in the introduction to this study and in H1.



(a) Larger subnetwork (n = 568, $|E|$ = 7731)



(b) Top three users (n = 82, $|E|$ = 100)

Figure 2: User-to-hashtag co-occurrence networks. Nodes are sized by total degree centrality; colors denote the type of node (users and hashtags); link widths are scaled by weight.

Negative	Positive 0	1	2	3	4
0	35.51%	6.15%	4.29%	0.17%	0.01%
-1	23.33%	4.16%	0.88%	0.05%	0.01%
-2	16.54%	2.39%	0.67%	0.08%	
-3	3.61%	1.29%	0.49%	0.01%	
-4	0.28%	0.08%			

(a) Tweets containing Migrant hashtags

Negative	Positive 0	1	2	3	4
0	46.49%	7.81%	5.27%	0.25%	0.01%
-1	17.42%	4.87%	1.69%	0.12%	0.01%
-2	8.16%	2.88%	0.72%	0.05%	
-3	2.86%	0.85%	0.28%	0.02%	
-4	0.19%	0.05%	0.02%		

(b) Tweets containing Refugee hashtags

Negative	Positive 0	1	2	3	4
0	43.32%	6.28%	9.24%	0.10%	0.01%
-1	16.86%	5.90%	0.93%		
-2	12.76%	1.08%	0.25%		
-3	1.99%	0.34%	0.15%	0.01%	
-4	0.77%	0.01%			

(c) Tweets containing both Migrant and Refugee hashtags

Figure 3: Sentiment percentages in tweets containing specific hashtags.

Table 3: Regression of sentiments

	Dependent variable:			
	ordered logit regression			*OLS*
	Positivity	Negativity	Sentiment	Intensity
Constant (i.e. refugee & migrant hashtags)				**0.996*****
				(0.011)
Migrant hashtags only	−0.0003	**0.040***	−0.022	**0.058*****
	(0.020)	(0.017)	(0.017)	(0.008)
Refugee hashtags only	**0.237*****	**−0.508*****	**0.562*****	**−0.136*****
	(0.028)	(0.022)	(0.022)	(0.011)
Observations	369,483	369,483	369,483	369,483
R^2				0.002
Adjusted R^2				0.002
Log Likelihood	-271,640	-389,817	-518,520	
F Statistic				349*** (df = 2; 369480)
Note:				$^{\wedge}p$<0.1; $^{*}p$<0.05; $^{**}p$<0.01; $^{***}p$<0.001 Constants for the ordered logit models not reported

Next in Table 4, as mentioned in the methods section, we regress popularity, influence of the user, and influence of the tweet (i.e., retweets) on sentiment measures, while controlling for the hashtag usage, in order to characterize these dependent variables and test H2 and H3. Sentiment Intensity of a tweet does not appear to have a main effect in characterizing the popularity of the tweeter. However, this is largely due to the interaction of the intensity and the tweet type, based on hashtag use. Those that tweeted with just one kind of hashtag and with muted sentiment tended to be more popular, given the negative and significant unstandardized coefficients of −0.066 for use of refugee hashtags and −0.086 for use of migrant hashtags. This points towards less Intensity employed by popular users, particularly those focusing their discussion on either refugee or migrant. Thus, H2 is unsupported, and in fact the

Table 4: Regression of popularity and influence

	Dependent variable:		
	Popularity	Influence	Retweets
Constant	**6.032*****	**0.921*****	**0.253*****
	(0.041)	(0.018)	(0.036)
Intensity	0.005	**−0.023**^	**−0.063****
	(0.028)	(0.012)	(0.024)
#Refugee hashtags only	**0.126*****	**−0.123*****	**0.124*****
	(0.030)	(0.013)	(0.026)
#Migrant hashtags only	**0.069****	**0.057*****	0.010
	(0.022)	(0.010)	(0.021)
Positivity	0.007	**−0.010**^	**0.040****
	(0.014)	(0.006)	(0.012)
Negativity	−0.006	0.004	**0.060*****
	(0.015)	(0.006)	(0.013)
Intensity and #Refugee	**−0.066****	**0.020***	−0.010
	(0.022)	(0.009)	(0.019)
Intensity and #Migrant	**−0.085*****	**−0.038*****	−0.008
	(0.017)	(0.007)	(0.016)
Observations	369,483	369,483	102,773
R^2	0.001	0.002	0.001
Adjusted R^2	0.001	0.002	0.001
F Statistic	58*** (df = 7; 369475)	85*** (df = 7; 369475)	20*** (df = 7; 102765)
Note:			^p<0.1; *p<0.05; **p<0.01; ***p<0.001

opposite effect is detected. We also observe a significant positive effect of each hashtag use, indicating that use of both hashtags is associated with less popular users. Those that are more popular tend to be more focused and slightly more polarized (as inferred through Table 3) than those who jointly employ the refugee and migrant hashtags. Meanwhile, popularity does not seem at all characterized by positivity or negativity separately in tweets.

Further, Intensity alone and interacting with the exclusive use of refugee and migrant hashtags does significantly characterize the influential quality of a user; however, the effects are mixed. The use of refugee hashtags alone appears characteristic of less influential users, but this effect is tempered by those tweeting with more emotional intensity (via the positive interaction). Conversely, the use of the migrant hashtag is characteristic of more influential users, the positive effect of which is also tempered by emotional intensity (via the negative interaction). Overall, more influential users are characterized by less emboldened statements, which also mute the extent to which the refugee and migrant hashtags distinguish the influential quality of a user. These observations provides indirect evidence for disconfirming H3, that influential tweets are associated with higher sentiment intensity. Here, we see that the influential quality of the user is associated with less sentiment intensity.

However, the influential quality of a tweet itself also lies in its spread, via retweeting. Here, we more clearly observe that the intensity of a tweet does indeed detract from its spread. Thus, we can claim that H3 is disconfirmed when considering both the influential quality of the tweet and the user.

Controlling for the negative influential effect of intensity, both positivity and negativity contribute significantly to retweeting, indicating singularly positive or negative tweets (i.e., not harboring mixed sentiment) mitigate the reduction of influence incurred by more emotional tweets. The effects of positivity and negativity differ, with negativity's contribution being higher ($0.060 > 0.040$); their difference being significant ($Z = -63.90, p < .001$). Thus, we find that negativity for tweets carrying hashtags related to refugee, migrant, or both contributes more to retweeting than positivity, thereby disconfirming H4.

5 CONCLUSION

Social media platforms only exist through the continual and growing participation of millions of users, and depend on individual and collective participation and creation of content. Thus, social media responses to societal events can lead to empowered, uninhibited, and impactful opinion expression. Consequently, social media discussions can undermine public support, steer public opinion, and influence reactions to the refugee crisis or even the refugees themselves.

The debate of the refugee/migrant crisis on social media, and on Twitter in particular, has been heated since the news reports and subsequent viral sharing of an image of the death of the toddler Alan Kurdi on Sept. 4, 2015. Since then, sentiments in social media discussion have been associated with differential use of relevant labels surrounding the crisis, including 'refugee' and 'migrant' (e.g., on YouTube [25]). The biases inherent in terms such as 'refugee' and 'migrant' have led to our investigation on the impacts of these biases on important characteristics of Twitter content.

The network analysis methods employed in this paper have revealed important aspects of hashtag usage, as well as interconnections between users and hashtags they employed. Here, one of our main findings are that the Twitter debate on this crisis –

captured by our data set – has been predominantly focused on refugee-related hashtags. Also, by employing bimodal network analysis, we were able to uncover the distinct position of the most active and seemingly central user, whom upon close inspection is rendered structurally and topically marginal to the refugee crisis debate, and perhaps uninfluential.

In order to further investigate whether the sentiment of this debate was a more sympathetic — as suggested by our proposed demarcation between the "deserving" refugee versus the "undeserving" migrant, we employed sentiment and regression analysis. The assumption that tweets containing the refugee-related hashtags would carry more positivity and less negativity than migrant-related hashtags (H1) was confirmed. Additionally, the sympathetic bias for the refugee is qualified by its lesser intensity, while the controversial nature of the migrant is slightly emphasized by more intense sentiment in the corresponding tweets.

Users and their tweets have the power to influence others, as evidenced by multiple studies. However, the expectations of positivity and sentiment intensity characterizing popular and influential users and tweets were not met (H2, H3, and H4). In fact, the results showed largely opposite effects. Popular users and influential tweets are characterized by less emotional intensity and slightly less positivity when it comes to the debate on the refugee/migrant crisis. These findings may be more characteristic of controversial topics (such as the refugee/migrant crisis), whereby the public nature of tweets in conjunction with the concept of the deserving refugee mutes outrageous or hyperbolic claims and opinions.

The popularity of a user and influence of a tweet (via retweeting) appear to be more characterized by the use of refugee-only hashtags. That is, users (both popular and retweeters) have been paying more attention to the refugee-labeled perspective of the crisis and not migrant perspective. However, this observation alone does not necessarily confirm the sympathetic bias towards the refugee; that bias can be observed through the findings supporting H1, above.

The results presented in this paper prompt us to further explore the relationship between the network typology, the types of information shared by Twitter users, and the role sentiment intensity in the refugee crisis debate. Our work aims to bring a contribution towards a better understanding of how displaced people are framed and how various actors respond to them. Future directions for this research will include larger data samples with wider time horizons, allowing for comparisons across time. Also, the sentiment and socio-semantic perspectives will be merged and focused on influential Twitter users, and how they are central to the crisis debate.

The dataset analyzed in this study pertains to English language Tweets posted in the span of only two days, and thus it limits the extent to which we can generalize our findings in several ways. Firstly, many of the countries affected by the refugee/migrant crisis are not anglophone and thus the framing of the crisis in these countries may differ. As such, a more comprehensive understanding of the overall perception of this crisis would require the inclusion of tweets that employ the languages of all the countries affected by the influx of displaced people. Secondly, the relatively short time span covered by our data set (only 2 days), although yielding a considerable number of tweets, can be considered limiting in terms of the wider social media debate on the refugee/migrant crisis. This is way future plans for our work involve the inclusion of multiple data samples, spanning longer time periods, to delve into patterns of opinion and influence and their evolution across time.

The sentiment analysis method employed in this article comes from Thelwall [40] and uses a human-coded lexicon of words and phrases specifically built to work with online social (media) data. The proposed algorithm, SentiStrength, utilizes this human-coded lexicon to identify the sentiment strength of informal text (e.g., tweets, status updates, YouTube comments). Although SentiStrength has proven relatively accurate and consistent in analyzing social media data, its results remain confined to the fixed set of words that appear in its lexicon. This may pose problems when dealing with online textual data, where new expressions and jargon constantly emerge.

As social media become more prevalent communication tools in times of crisis, studies jointly investigating discussions as well as social structures – such as this one – become increasingly valuable by offering insights into the nature and direction of these discussions, public actors, and their sentiments surrounding the crisis.

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