

Refugee or Migrant Crisis? Labels, Perceived Agency, and Sentiment Polarity in Online Discussions

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Ju-Sung Lee¹ and Adina Nerghes²

Abstract

In recent years, increasing attention has been dedicated to the hazardous and volatile situation in the Middle East, a crisis which has pushed many to flee their countries and seek refuge in neighboring countries or in Europe. In describing or discussing these tragic events, labels such as “European migrant crisis” and “European refugee crisis” started being widely used by the media, politicians, and the online world alike. The use of such labels has the potential to dictate the ways in which displaced people are received and perceived. With this study, we investigate label use in social media (specifically YouTube), the emergent patterns of labeling that can cause further disaffection and tension or elicit sympathy, and the sentiments associated with the different labels. Our findings suggest that migration issues are being framed not only through labels characterizing the crisis but also by their describing the individuals themselves. Using topic modeling and sentiment analysis jointly, our study offers valuable insights into the direction of public sentiment and the nature of discussions surrounding this significant societal crisis, as well as the nature of online opinion sharing. **We conclude by proposing a four-dimensional model of label interpretation in relation to sentiment—that accounts for perceived agency, economic cost, permanence, and threat, and identifies threat and agency to be most impactful. This perspective reveals important influential aspects of labels and frames that may shape online public opinion and alter attitudes toward those directly affected by the crisis.**

Keywords

social media, sentiment analysis, topic modeling, labels and frames, European refugee crisis

Introduction

Since April 2015, when five boats carrying refugees sank in the Mediterranean Sea, killing over 1,200 people, increasing media coverage has been dedicated to the hazardous and volatile situation in the Middle East, a crisis which has pushed many to flee their countries and seek refuge in neighboring countries or in Europe. In reporting or discussing these tragic events, and their repercussions on European societies, labels such as “European migrant crisis” and “European refugee crisis” started being widely used by media and politicians alike. Describing the crisis and its events, through such labels, frames the influx of displaced people into Europe in specific ways. For example, while a label such as “refugee” portrays people fleeing armed conflict or persecution, “migrant” describes people making a conscious decision to leave their country and seek a better economic situation elsewhere. Such labels, then, serve as frames that alter perceptions and perhaps even influence behaviors and may have serious consequences for the lives and safety of those displaced individuals;

they can undermine public support, steer public opinion, and frame the debate on how the world should understand and react to this crisis (de Vreese, 2005; O’Neill, Williams, Kurz, Wiersma, & Boykoff, 2015).

The use of labels has the potential to shape the range of possibilities for understanding what the story is, and the way migrants and refugees are perceived. Negatively labeling and framing refugees and migrants may lead to serious problems in the host societies, where perceptions are significantly influenced. For example, as shown by the report issued by the European Commission (Canoy et al., 2006), public perception

¹Erasmus University Rotterdam, The Netherlands

²KNAW Humanities Cluster, The Netherlands

Corresponding Author:

Ju-Sung Lee, Media & Communication, Erasmus University Rotterdam,
P.O. Box 1738, Rotterdam 3000 DR, The Netherlands.
Email: lee@eshcc.eur.nl



of migration tends to be negative throughout Europe, an issue that has become increasingly exigent (ESS ERIC, 2017). Thus, labels and frames provide indications of the ways in which displaced people are received and perceived across Europe and beyond.

The labels used by the media, politicians, and even online sources clearly indicate that migration issues are being framed not only by the labeling of the crisis and events but also by the labeling of individuals themselves. Employing certain labels, keywords, or stock phrases (e.g., refugee, refugee crisis, migrant, migrant crisis, immigrant, immigrant crisis, Syrian, Syrian migrant, Syrian refugee, asylum seeker, etc.) in communication contexts may affect receivers by emphasizing different frames for evaluation of the same issue or event (e.g., Chong & Druckman, 2007; Druckman, 2011; Entman, 1993; Goffman, 1974; Rohan, 2000).

Through framing, certain features of a story are selected while others are excluded (Iyengar, 1987); thus, frames may shape people's interpretation of that story by making certain perspectives more salient (Hallahan, 1999; Iyengar, 1987; Pan & Kosicki, 1993). Drawing from the work of Goffman (1974), we understand that frames elicit, as well as constrain, the interpretative activities of audiences (Pan & Kosicki, 1993). Entman (1993) 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" (p. 52). By highlighting certain characteristics of an issue and hiding others, framing reflects the emphasis of the author.

While recognizing the importance of frames and frame analysis, in this article, we focus on the use of labels. The term "frame labeling" acknowledges the close relationship between labeling and framing (Knoll, Redlawsk, & Sanborn, 2011) and disambiguates our focus from the problematic conceptualization of generic and variable framing (Cacciatore, Scheufele, & Iyengar, 2016). In other words, we consider labels as the building blocks in the creation of frames, and we further postulate that the selection and use of labels is a crucial and important instrument in the process of framing particular events and individuals.

Whether rooted in cognitive psychology (e.g., Kahneman & Tversky, 1984; Tversky & Kahneman, 1985) or the social sciences (e.g., Druckman, 2011), most studies focus on the analysis of frames and labels used in news media or public discourse, and their varying effects on people's choices or attitudes. There are many examples of studies investigating media use of frames and labels on migration issues (e.g., Haynes, Devereux, & Breen, 2008; Horsti, 2007; Roggeband & Verloo, 2007; Roggeband & Vliegthart, 2007), as well as examples of studies investigating their effects (e.g., Augoustinos & Quinn, 2003; Brader, Valentino, & Suhay, 2008; Brewer, 2001). However, in this study, we take a different approach by uncovering the use of labels in social media and the sentiment surrounding these labels, with the

understanding that certain labels are employed for different purposes and can evoke different connotations (O'Doherty & Lecouteur, 2007). Thus, we draw a parallel between the various labels attributed to this recent crisis by laypeople in social media and the various sentiments associated with each label.

The battle over the words used to describe migrants, or the "struggle over framing" (Gamson & Wolfsfeld, 1993), does not take place only in mass media or public discourses. Rhetorical framing labels have become an integral part of social media and the online world. An example is the Wikipedia entry on the topic of the "European migrant crisis," which begins by stating "The European migrant crisis *or* European refugee crisis began in 2015 [. . .]" (Wikipedia, 2015). The use of these two (distinct) labels joined by "or" seems to imply they are equivalent or synonymous. However, as proposed earlier, the terms "migrant" and "refugee" denote very distinct characteristics of the individuals labeled as such. These labels and others like them constitute social categorizations, that are discursively and socially constructed (Augoustinos, 2001). Because "language, thought, and actions are inextricably linked" (Hardy, 2003), labels surrounding migrants and refugees, and their implied categorizations, may consequently explicitly or even subliminally encourage specific actions, including marginalizing practices (Fairclough, 2000; O'Doherty & Lecouteur, 2007). The examination of marginalizing discourse is of great importance in a time of high people mobility across borders (Hopkins, Reicher, & Levine, 1997; O'Doherty & Lecouteur, 2007).

Through this study, we aim to uncover label use in social media surrounding the recent influx of displaced Middle-Eastern individuals, the emergent patterns of labeling that can cause further disaffection and conflicts or elicit sympathy, and the sentiment associated with the different labels. For our data collection, we focus on YouTube, one of the most frequently visited Internet sites that stimulate social interactions through user-generated content such as comments and replies to comments. Our guiding research questions are then as follows:

RQ1: What are the patterns of label use in online discussion of the European refugee/migrant crisis?

RQ2: What are the sentiments associated with these labels?

RQ3: How are these labels structured and embedded in the European refugee/migrant crisis online discussions?

Previous studies distinguish various social characterizations of migrants and refugees. Refugees have been depicted by the media, political discourse, and public opinions as taking passive roles and rarely as active agents (Bradimore & Bauder, 2011; Kempadoo, 2005; Van Dijk, 1988). That is, their dire situation compels them to flee their home countries for survival, so they are considered deprived of agency. Migrants, on the contrary, are portrayed as crossing borders mainly seeking benefits of the host country's economy and

tax payers (Bradimore & Bauder, 2011). Hence, they have been labeled as economic, and not “real,” refugees (Van Dijk, 1988), seeking upward mobility while creating public anxiety over an incoming mass of poor refugees who would become burdens of the welfare state (Ana, 1999; Baker & McEnery, 2005; Greenberg, 2000; Hardy, 2003; Santa Ana, 2002). This “economic dimension” has been used to delegitimize refugee claims by categorizing them as economic migrants (Greenberg, 2000). Furthermore, a distinction can be drawn between the implications of “migrant” and “refugee” in that migrant implies transience while refugee connotes permanence in residency in a host country (Darling, 2014; Dustmann, Fasani, Frattini, Minale, & Schönberg, 2017; Lee & Nerghes, 2017; Naimou, 2016).

Finally, the portrayals of migrants, refugees, and immigrants alike are often fraught with negative, often strongly negative, rhetoric—stripping them of any positive characteristics and impugning them to be exploiters or headed toward criminal pathways (Bradimore & Bauder, 2011; Cohen, 2002; van Dijk, 1998)—which is often symptomatic of scapegoating that channels host societies’ fears and anxieties (Cohen, 2002). Hence, previous research has associated refugees and migrants with characteristics or dimensions of agency, economic cost, permanence, and more severe societal costs, such as the threat of criminality. This leads to our last guiding research question:

RQ4: How do these four dimensions—agency, economic cost, permanence, and the threat of criminality—impact the sentiments surrounding the labels used in the European refugee/migrant crisis online discussions?

Social Media and Public Opinion

In the last few decades, the ways in which people both access and share information about opinions, attitudes, and behaviors have gone through immense transformations due to the mainstream adoption of social media. Social media platforms have fostered a remarkable shift toward increased user participation in creating publicly available content (photos, videos, audio, and textual information) and user engagement with content shared by others (Gill, Arlitt, Li, & Mahanti, 2007; Heckner & Wolff, 2009).

While the exact role of this new media is still being debated, there is no denying that for many people, social media has become a source of information, significant influencer of emotions, and an avenue for organizing activities and making decisions (Sobkowicz, Kaschesky, & Bouchard, 2012).

Research has shown that social media serves as an alternative public space, where users can participate in discussing a societal crisis (Mäkinen & Wangu Kuira, 2008), and offers a new avenue for understanding public opinion that is more socially and conversationally based (Anstead & O’Loughlin, 2015). As a public space, social media has the potential to

augment personal opinion expression and promote exchanges of ideas (Papacharissi, 2002). Social media platforms have become the ideal vehicle and information base to gauge public opinion, for example, in politics and business, as well as to build support for initiatives, public figures, or brands (e.g., Anstead & O’Loughlin, 2015; Mejova & Srinivasan, 2012; Zeng, Chen, Lusch, & Li, 2010).

Hence, social media platforms allow for a continuous look at opinion, attitudes, and behaviors. The relevance of social media is further highlighted by its alignment and impacts to offline-measured behavior and opinions (Mejova & Srinivasan, 2012; O’Connor, Balasubramanyan, Routledge, & Smith, 2010; Walther, DeAndrea, Kim, & Anthony, 2010). Among the myriad of platforms, Facebook, YouTube, and Twitter are among the most popular (Statista.com, 2018) and most often studied. Given their different affordances, opinion expression varies across the platforms as does the generalizability of research findings. However, some research reveals similarities in public opinion and sentiment across the three platforms (e.g., Smith, Fischer, & Yongjian, 2012) and also highlights the relevance of YouTube comments, in particular, in that they best match actual public opinion (Mejova & Srinivasan, 2012). This is due to the high level of anonymity YouTube offers, resulting in rhetoric that is less censored and putatively more honest (Halpern & Gibbs, 2013; Hanson, Haridakis, Cunningham, Sharma, & Ponder, 2010). For these reasons, we focus our attention on the discourse on the refugee/migrant crisis found on YouTube.

YouTube

YouTube is a video-sharing platform that has become one of the most frequently visited Internet sites, with over 1 billion monthly users, watching a total of 6 billion video hours per month (Gill et al., 2007; Heckner & Wolff, 2009; Socialbakers.com, 2018). The popularity of YouTube can be attributed in part to the online environment it provides, allowing users to both retrieve and post content. In this sense, YouTube can be considered a hybrid form of communication because it serves as mass media, allowing for reach from one-to-many, but also as an interpersonal form of communication, allowing users to engage in one-to-one dialogues, thus stimulating social interactions (Lillie, 2008).

Previous Research

Scholarly interest in YouTube has been gaining momentum. Recent efforts have increasingly focused on studying YouTube user behavior by measuring video popularity and video content through quantitative methods. For example, Paolillo (2008) analyzed user profiles and identified that certain types of content were cultivated by users from particular social groups with shared characteristics. Similarly, Canali, Colajanni, and Lancellotti (2010) assessed the strength of links between users and found that certain users had a

significantly higher proportion of fans in relation to invited friends. Chatzopoulou, Sheng, and Faloutsos (2010) analyzed over 37 million videos, investigating properties such as view counts, number of comments, ratings given, and the number of times a video is tagged as a “favourite,” in order to uncover the best indicators of video popularity. Their results suggest that favorite-ing, commenting, or rating was a stronger indicator of popularity than simply viewing a video. Kousha, Thelwall, and Abdoli (2012) provide a more comprehensive review of quantitative studies investigating YouTube videos in a multitude of domains including marketing, medicine, and management.

Qualitative studies investigating YouTube data have been emerging as well. For example, Lange (2007b) analyzes video-sharing behavior, while Kousha et al. (2012) examines the type of YouTube videos cited in academic publications. However, most of these studies, whether qualitative or quantitative, focused on the video type, content of the video itself, or video statistics (e.g., number of views, likes, dislikes, etc.), rather than on the content of user comments. YouTube comments have, thus far, been comparatively understudied in relation to other aspects of the site. The large number of comments, and the variable quality in terms of spelling, grammar, and expression, has presented considerable difficulties for such studies. However, as Siersdorfer, Chelaru, Nejdil, and San Pedro (2010) argue, the YouTube comment section “reflects to a certain degree the ‘democratic view of a community.’” Research has also found that YouTube comments appear to reflect real-life communication behavior (Schultes, Dorner, & Lehner, 2013). Thus, YouTube commentary may serve as a lens for public opinion on issue importance, or even as a venue for user mobilization, learning, and opinion-formation (Jones & Schieffelin, 2009; Kirk & Schill, 2011; Porter & Hellsten, 2014).

The capability of YouTube to stimulate social interactions through user comments makes it a valuable site for investigating the use of labels in response to the issues arising from the European refugee (or migrant) crisis. Social media platforms, such as YouTube, exist and depend on the continual co-creation of content from millions of participants. Social media responses to societal events—in the form of comments, for instance—entail self-expression (positive or negative), providing emotional support, reminiscence, grieving, and advice, as well as direct comments on multimedia content, such as the YouTube video itself (Madden, Ruthven, & McMenemy, 2013). Such responses are often characterized by relative anonymity that may lead to expressions of empowered and uninhibited opinion (Halpern & Gibbs, 2013).

YouTube users believe that sensitive or uncomfortable topics are more easily discussed in online settings (Lange, 2007a). Hence, YouTube comments have the potential to expose the ways in which labels are used and the affective content surrounding them. While labels themselves can be positive or negative, we also explore the sentiment of the content surrounding the various labels employed by YouTube

users, the emergent topics in these comments, and how the most prominent labels manifest in these topics. By analyzing comments and replies posted to two videos that propose opposing perspectives on the recent events of the refugee/migrant crisis, we also account for the effects the tone of a video may have on user responses. Investigating the use of labels in social media commentary may uncover discussions of alternative perspectives (Milliken & O'Donnell, 2008).

Data and Methods

For our analysis, we selected the two most popular (based on the number of views on 22 October 2016) YouTube videos using “refugee crisis” and “migrant crisis” as our search strings. The first video selected is titled “The European Refugee Crisis and Syria Explained,”¹ and has been viewed over 10 million times. This is a 6-min video published on 17 September 2015 that offers an objectively sympathetic perspective to the crisis, through animation, voice-over, and a musical score. In all, 46,313 publicly accessible user responses (i.e., comments and replies) posted to this video were collected. We will further refer to the corpus of comments ($n=16,719$) and replies ($m=29,594$) posted to this video, and also the video itself, as *refugee crisis* or *RC*.

The second video we collected is titled “What Pisses Me Off About the European Migrant Crisis”² and has been viewed over 700,000 times. Published on 2 September 2015, this video is a 28-min monologue by Stefan Molyneux, a popular figure on YouTube with over 600,000 subscribers.³ As the title suggests, the tone of this second video is very different from the RC video, presenting a vehement and highly negative outlook on the impact of economic, cultural, and religious differences between refugees and the host societies. A total of 13,871 publicly available user responses posted to this video have been included in our corpus.⁴ We will further refer to the corpus of comments ($n=4,702$) and replies ($m=9,169$) posted to this video (as well as the video itself) as *migrant crisis* or *MC*. For the purposes of this article, “comments” refer to both the videos’ comments and their replies.

Both the RC and MC corpora were collected using the Netvizz YouTube Data Tool (Rieder, 2015) and were cleaned prior to analysis; specifically, noise-words, punctuation, and numbers were removed.⁵ In addition, all words were lower-cased, stemmed (i.e., words were reduced to their morphemes, such as plurals converted to singular forms),⁶ and spelling was checked for all key labels.⁷ While YouTube comments appear in a public forum and may be considered to be “open text” and authors of those comments should have no expectations of confidentiality according to YouTube’s terms of service, consideration of privacy risks ought to be taken, especially given the impracticalities of acquiring full consent (boyd & Crawford, 2012; Reilly, 2014; Townsend & Wallace, 2016). Therefore, we maintain those authors’ privacy and mitigate risks of exposure and harm by omitting

Table 1. Broader Codes.

Code	Labels
Refugee	Refugee, refugee crisis
Syrian	Syrian, syrian migrant, syrian refugee
Migrant	Migrant, migrant crisis
Immigrant	Immigrant, immigrant crisis
Threat	Jihadist, terrorist, criminal, rapeegee

any mention of their usernames from this study as well as omitting specific comments, with the exception of a few selected comments (anonymized) used as exemplars in the appendix. Furthermore, the results presented in this article render it near impossible to identify specific users.

The analysis of this study focuses on those comments containing labels that describe various aspects of the refugee/migrant crisis: refugee, refugee crisis, migrant, migrant crisis, immigrant, immigrant crisis, syrian, syrian migrant, syrian refugee, asylum seeker, jihadist, terrorist, criminal, scum, muslim, islam, and rapeegee. We refer to both the unigrams and bigrams (i.e., single- and two-word phrases) as “labels” and each of these labels are exclusively coded. For example, the label “refugee crisis” will not also be coded as “refugee.” In selecting these labels, a unique concept (unigrams and bigrams) list was generated and parsed by the authors to identify those labels directly relevant to the topic under investigation. Furthermore, to capture the broader uses of the identified labels, we code umbrella indicator variables for groups of labels shown in Table 1, and we will subsequently refer to these as “codes.”

Our methodology includes both sentiment analysis and topic modeling on the corpus of YouTube comments of both videos, as well as regression analysis of sentiments on codes. For identifying patterns of label use (RQ1), we employ a statistical analysis on labels’ frequencies and their proportions.

Sentiment Analysis

Sentiment analysis is used to uncover the opinion valences associated with the labels employed in the comment threads of the RC and MC, in order to provide an answer to RQ2. For this, we employ Thelwall’s SentiStrength (Thelwall, 2013; Thelwall, Buckley, Paltoglou, Cai, & Kappas, 2010), which provides scores for two dimensions of sentiment (positivity and negativity) per emotional term and phrases within the comment.⁸ Since we are interested in *how* those labels are discussed, their accompanying sentiments are discounted from the sentiment scores. That is, the key labels were removed from the corpus prior to sentiment analysis in order to assess the sentiment of each comment absent any label.

Each of the positive and negative sentiment scores for a segment of text (i.e., a YouTube comment) range from 0 to 4 for capturing the extent of each sentiment dimension, with 0 indicating no sentiment.⁹ In addition, we calculate a new

variable for capturing sentiment on a single dimension ranging from -4 to +4:

$$\text{Sentiment} = \text{Positivity} + (-1)\text{Negativity}$$

Also, we capture the intensity of sentiment considering both the extent of positivity and negativity. This new measure is calculated as the Euclidean distance of the two dimensions score to neutrality (i.e., [0,0]):

$$\text{Intensity} = \sqrt{\text{Positivity}^2 + \text{Negativity}^2}$$

Regression Models. Regression models are used to reveal patterns of sentiment related to the use of codes (RQ2) as well as the relationships between label dimensions and sentiment (RQ4). These models predict the sentiment variables (dependent) using the umbrella codes and an indicator (or dummy) variable for the video from which the comment is associated (RC vs. MC), whereby values of 1 and 0, respectively, indicate comments from refugee and migrant crisis videos. Ordered logit (also known as ordinal logistic) regression models are used for the dependent variables of positive, negative, and the sum Sentiment scores as these take on integer values and the differences between scores have some subjective bearing. An OLS ((ordinary least squares) regression model is employed to predict the Intensity of sentiment as this variable takes on non-discrete values. These models are run on the entire corpus of both RC and MC comments.

Topic Modeling

Topic modeling and the analysis of networks of topic members can reveal prominent themes, their inter-connectivity, and the labels’ usage within those themes (RQ3). For this, we employ latent Dirichlet allocation (LDA) (Blei, Ng, & Jordan, 2003), a three-level hierarchical Bayesian model, as implemented in the MALLET software (McCallum, 2002). Topic models are a class of automated text analysis tools that seek to identify, extract, and characterize the various latent topics (i.e., themes) contained in collections of texts. More specifically, topics are identified based on word co-occurrence patterns across a corpus of text documents, where a cluster of words that co-occur frequently across a number of documents constitute a topic. Based on the idea that documents are collections of topics—in which a topic represents a probability distribution over words—topic models connect words with similar meanings and differentiate between uses of words with multiple meanings. Each topic is separately meaningful and represents a consistent cluster of correlated terms (Blei et al., 2003; Griffiths & Steyvers, 2002, 2003, 2004; Hofmann, 1999, 2001). For this study, each comment is considered a distinct document.

When fitting the LDA topic model to a collection of text documents, the analyst needs to specify the number of topics to be identified. This selection generally implies exploration of

different solutions to achieving the best fit. Based on the diagnostics reported in Appendix 4, as well as a qualitative examination of the resulting topics, we settled on an eight topics solution for each sub-corpus (described below), running the algorithm for 5,000 iterations with the hyperparameter $\sum\alpha=5$. However, fewer than eight topics are reported because several topics contain non-English terms and/or have low fitted weights (i.e., prominence). Finally, topics are not mutually exclusive; member words can be included in more than one topic.

For each of the discussion threads (RC and MC), we infer a set of topics based on a partition of each corpus according to the most negative and most positive comments, in order to uncover distinct topics associated with opposing ends of the sentiment spectrum and compare the topics surrounding the sentiment-laden discussions for the videos. Here, we consider those comments both containing and not containing the labels; future analyses will consider only those comments containing the selected labels. For negative comments, we consider those with Sentiment (sum) scores ≤ -3 ($n_{RC}^+ = 4,370, n_{MC}^+ = 698$) and for positive comments, we consider scores $\geq +2$ ($n_{RC}^- = 2,441, n_{MC}^- = 1,109$), due to there being fewer overall positive comments.

Network of Topic Members. The word membership within topics constitutes a bipartite, topic-to-word (TW) network. One can “fold” such a network by multiplying its transpose to itself to obtain a word-to-word (*WW*) network in which linkages represent words co-occurring within the same topic (or matrix cells) and also indicate the extent of the co-occurrence; the matrix calculation is $WW = (TW)^T \times TW$. This transformation also exposes words that span multiple topics, revealing concepts (i.e., words) that are employed in different contexts (i.e., topics). Hence, analyzing networks of topic members, for the most positive and the most negative comments in each of the videos in our data set, reveals overlaps in topics as well as the extent of separation within the more positively laced and also the more negatively laced discussions.

The networks are visualized using the software program Gephi (Bastian, Heymann, & Jacomy, 2009) arranged via the Force Atlas algorithm (Bastian et al., 2009) and colored according to the Louvain community detection algorithm (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). Nodes having the same color occur in communities in which more edges connect members within the community than members of different communities. Nodes and their labels are sized according to their betweenness centrality scores, which captures the extent to which a node lies in the shortest paths between all pairs of nodes, and indicates the extent of their connectivity across topics.

Results

In Table 2, the frequencies (or counts) of each of the labels we investigate are reported, along with those of the umbrella codes, and proportions of occurrence, relative to the total

Table 2. Frequency and Proportions of Labels and Codes.

	Samples (n)		Prop. (Pr)		
	RC	MC	RC	MC	
Labels					
Refugee	9,020	1,206	.19	.09	***
Refugee crisis	474	69	.01	.00	***
Migrant	1,482	608	.03	.04	***
Migrant crisis	57	76	.00	.01	***
Immigrant	1,972	797	.04	.06	***
Immigrant crisis	15	28	.00	.00	***
Syrian	2,456	343	.05	.02	***
Syrian migrant	22	6	.00	.00	
Syrian refugee	835	65	.02	.00	***
Asylum seeker	162	81	.00	.01	***
Jihadist/terrorist	1,866	213	.04	.02	***
Criminal	533	102	.01	.01	***
Scum	236	105	.01	.01	***
Muslim	5,210	1,330	.11	.10	***
Islam	2,895	858	.06	.06	
Rapeegee	83	1	.00	.00	***
Codes					
Refugee	9,737	1,290	.21	.09	***
Migrant	1,528	660	.03	.05	***
Immigrant	1,980	818	.04	.06	***
Syrian	3,073	402	.07	.03	***
Threat	2,326	300	.05	.02	***
ΣLabels	18,644	3,470	.40	.25	***
ΣComments	46,313	13,871			

RC: refugee crisis; MC: migrant crisis.

*** $p < .001$; bold indicates $Pr_{RC} < Pr_{MC}$; otherwise, $Pr_{RC} > Pr_{MC}$.

number of comments in each video, in order to answer RQ1. In addition to the labels appearing under the umbrella codes, statistics on additional frequently occurring labels are reported; these are relevant to this article's topic but do not directly fall under any of the codes.¹⁰

The individual labels (e.g., “refugee”) naturally occur more frequently than the bigrams (e.g., “refugee crisis”), even under our exclusive coding. As the RC video addresses both the refugee crisis and Syrian migration, both “Refugee” and “Syrian” umbrella codes are highly represented in the video's comment thread. While the MC video's comments also display a relatively high proportion of comments with “Refugee” related terms, the next most common terms relate to “Immigrant” and “Migrant,” highlighting the pervasiveness of the “Refugee” frame, even in content that indirectly addresses it. This distinction between the two videos is further highlighted by the results of the proportions tests, denoted by the significance of the χ^2 s, accompanying each pair of proportions in the table.

The predominance of the “refugee” label and the “Refugee” code in both videos would suggest a sympathetic tone in many of the comments in our corpus. As discussed in our introduction, the term refugee denotes individuals

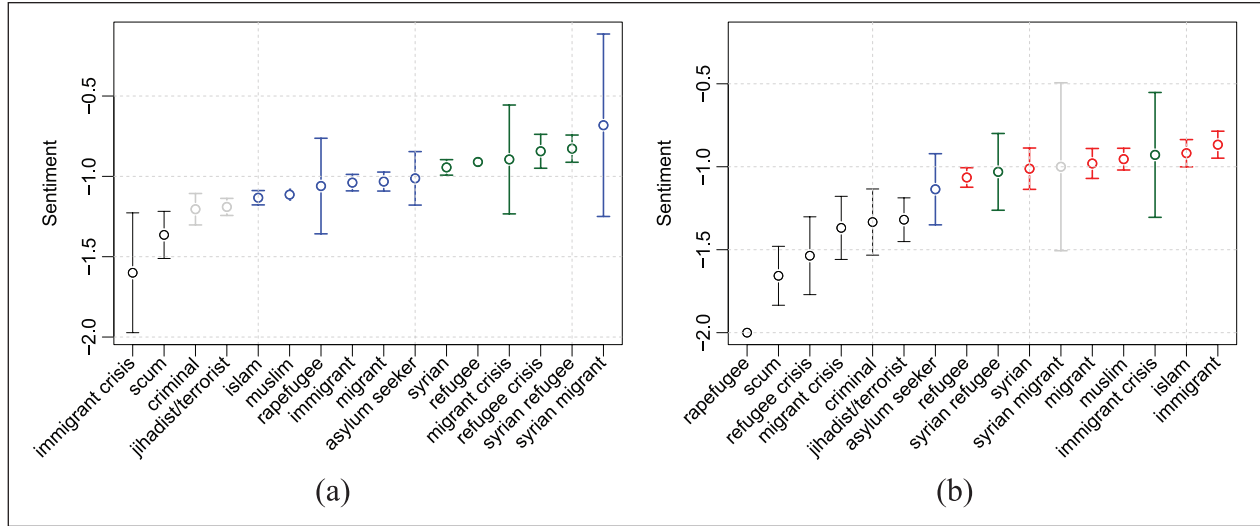


Figure 1. Sentiment of comments containing key concepts for refugee and migrant crisis videos: (a) Refugee crisis video (RC) and (b) migrant crisis video (MC).

fleeing their native countries as a result of armed conflict or persecution. This particular finding raises questions about how this label is used, and what is the valence of the comments employing it. We return to this point when discussing our sentiment analysis results.

We also observe that the MC comments exhibit relatively higher frequency of “asylum seeker” that can denote either sympathy or antipathy as well as “scum,” a strictly negative term, raising preliminary expectation that the MC comments will have a more negative tone overall, in line with the tone of the MC video itself. Finally, the RC comments employ proportionally more labels than the MC comments. An inspection of the most frequent, non-noise unigrams (Table 7 in Appendix 2) indicates that the non-label words employed in the MC comments, which differ from the frequent RC unigrams, pertain to either general concepts like “world” or specific regions of concern like “germany.” That is, with the exception of Germany, the top terms in the MC discussion thread would seem to indicate less coherence of themes.

Sentiment Analysis Results

The analyses in this subsection focus on the sentiment scores assigned to comments, from both the RC and MC videos, containing the selected labels and thus address RQ2. The first analysis (Figure 1) reveals the unidimensional “Sentiment” scores and ordering of the labels. The error bars represent 95% confidence intervals (CIs), and the colors denote the significance in the difference of means (via t -tests) between the colored CI scores and the mean score of the comments containing the lowest scoring, relevant label: “immigrant crisis” for RC and “refugee crisis” for MC. The colors gray, blue, green, and red, respectively, denote increasing significance levels: $p < .10$, $.05$, $.01$, and $.001$.

In the figures, we observe that all average sentiments (and accompanying CIs) reside in the negative region of sentiment, showing that the sentiments in the majority of the comments containing the labels are negative. In fact, the mean sentiment of those comments containing any of the labels (not appearing in the figures), $M = -0.97$ (RC) and -0.99 (MC), 95% CIs $[-0.98, -0.95]$ and $[-1.02, -0.95]$, are similar across videos; thus, the sentiment of such comments do not appear to be obviously aligned to the starkly opposing tone of the videos themselves, at least at this general level. Still, these means together are significantly more negative than the mean sentiment from all other comments (i.e., those comments that do not contain any of the labels in Table 2). The latter set, however, still harbors some nominal level of negativity, $M = -0.55$ (RC), -0.59 (MC); $t(39922) = 33.3$, $p < .001$, 95% CIs $[-0.57, -0.54]$ and $[-0.61, -0.56]$, but the majority exhibits some level of positivity; that is, most comments retain a mixture positivity and negativity rather than being neutral or only negative).

While naturally, certain labels are expected to elicit higher negativity (such as “scum,” “criminal,” “jihadist/terrorist,” “rapefugee”) in both videos, even when discounting the sentiment in the label itself, others in the RC video comments are surprisingly negative, namely, “immigrant crisis,” and “immigrant,” indicating relative antipathy in the comment thread of the more sympathetic video (i.e., RC). Bigrams containing “syrian” appear to elicit the least negative (or most positive) sentiment in the RC video, suggesting more sympathy for their specific situation. Similarly, the labels describing individuals displaced by adverse situations are viewed less negatively than those labels indicating some degree of agency or opportunity (labels containing “immigrant” or “migrant”).

The labels of the MC comments exhibit a different ordering that is both surprising and not surprising. “Crisis” and the

Table 3. OLS Regression of Sentiments for Both Videos..

	Dependent variable			
	Ordered logit regression			OLS
	Positive	Negative	Sentiment	Intensity
Constant				1.711*** (0.011)
Asylum Seeker	0.123 (0.196)	0.435* (0.198)	-0.250 (0.187)	0.199 (0.133)
Refugee	0.504*** (0.055)	0.793*** (0.051)	-0.448*** (0.051)	0.560*** (0.036)
Syrian	0.346*** (0.074)	0.546*** (0.070)	-0.285*** (0.069)	0.375*** (0.048)
Migrant	0.674*** (0.066)	0.621*** (0.063)	-0.134* (0.063)	0.487*** (0.043)
Immigrant	0.382*** (0.093)	0.491*** (0.089)	-0.239** (0.088)	0.364*** (0.061)
Threat	0.464*** (0.106)	1.093*** (0.101)	-0.678*** (0.098)	0.714*** (0.069)
Is RC Video	-0.136*** (0.021)	-0.112*** (0.019)	0.019 (0.019)	-0.077*** (0.013)
Asylum Seeker × RC	0.409† (0.241)	0.138 (0.242)	0.122 (0.230)	0.198 (0.162)
Refugee × RC	-0.027 (0.059)	-0.213*** (0.056)	0.215*** (0.055)	-0.165*** (0.038)
Syrian × RC	0.0003 (0.088)	0.034 (0.084)	0.008 (0.083)	-0.015 (0.057)
Migrant × RC	-0.088 (0.078)	0.191* (0.075)	-0.199** (0.074)	0.061 (0.051)
Immigrant × RC	-0.143 (0.099)	-0.208* (0.095)	0.127 (0.094)	-0.160* (0.065)
Threat × RC	-0.065 (0.113)	-0.125 (0.108)	0.097 (0.105)	-0.122† (0.074)
Observations	60,184	60,184	60,184	60,184
R ²				0.058
Adjusted R ²				0.057
Log likelihood	-65,326	-85,760	-100,794	
F statistic				283*** (df= 13; 60,170)

OLS: ordinary least squares; RC: refugee crisis.

Constants for the ordered logit models not reported.

† $p < .1$; * $p < .05$; ** $p < .01$; *** $p < .001$.

sympathetic “syrian” related labels tend to be lower in the ordering compared to the RC video comments, which is consistent with the negatively alarmist tone of the video. However, “muslim” and “islam” are among the least negatively associated labels. The sentiment differences for each of these terms across videos, while small, are in fact significant ($p < .001$ in both cases). An inspection of the MC video comments containing “muslim” or “islam” reveals some sympathetic or reasonable discourse peppered throughout the threads. While these comments bear some negativity, they also exhibit some positivity. Some MC video discussants appear to counter the tone and claims of the video content.

In Table 3, the regressions of the sentiment measures on the umbrella codes in both videos, the RC video indicator (to distinguish the video thread), and their interactions are presented. We include an additional code “Asylum Seeker” due to its relevance and prominence in our data.¹¹ The notable effects in the models complement and elaborate on some of our earlier findings. In general, the codes are discussed more negatively than positively, which is not surprising given the topics of both videos. This also corroborates findings presented earlier in this article, that overall sentiment is more negative than positive. When comparing the coefficients predicting Positive and Negative, we see that the RC comments

with labels exhibit both less positivity and negativity than the MC's, resulting in slightly (but significantly) less intensity.

Threats naturally are the most provocative, and hence contribute highly to negativity both in its single dimension and overall sentiment, resulting in the highest effect on intensity. Still, the overall intensity of Threat is muted (weak significance) in the more sympathetic RC thread. The discussion of Refugee is also unsurprisingly intense, having the second highest intensity and high positivity and negativity. Upon inspection of the interaction terms, we see less negativity (higher sympathy) in the RC, muting their intensity. The labels under the Migrant code exhibit the highest positivity and third highest negativity, which almost cancel one another and result in a mild negative contribution to the overall sentiment and relatively moderate intensity. Interestingly, Migrant is discussed more negatively in the RC thread than the MC thread, when controlling for the other codes, along both the negative dimension and overall sentiment (indicated by the significant interaction effects). This is surprising given the differing tones of the two videos and the results of Figure 1, and may hint at counter-debates occurring in both videos.

The discussions that include Immigrant and Asylum Seeker are relatively muted, although expectedly, they exhibit either lower negativity or higher positivity in the RC discussions. While Asylum Seeker could arguably fit under the Refugee code, its significant predictions suggest its independence from Refugee. Meanwhile, comments containing the labels under the Syrian code only modestly add to the sentiment dimensions and intensity.

When comparing the ordering of codes by Sentiment and Intensity, we find some alignment: intensity is largely driven by negative sentiment. This speaks again to the controversial and tragic nature of these events and the content of the videos. Furthermore, Syrian, Migrant, and Immigrant contribute least to overall sentiment and intensity, in slightly different orderings for sentiment and intensity. These orderings can be placed in a larger context in which agency plays a role in determining the sentiment attached to the key labels in each of these broad codes. We revisit this discussion in our concluding section.

To further investigate what has been suggested to be dimensions or frames associated with the central actors of this crisis (i.e., displaced individuals) (Lee & Nerghes, 2017), we map the umbrella codes into the frames of Agency, Economic Cost, Permanence, and Threat. Here, Agency refers to actors having relatively higher agency in crossing borders (e.g., not in fear for their lives) as discussed by several authors (Bradimore & Bauder, 2011; Kempadoo, 2005; Van Dijk, 1988), Permanence refers to whether or not actors are expected to permanently reside in a host country (Darling, 2014; Dustmann et al., 2017; Lee & Nerghes, 2017; Naimou, 2016), while Economic Cost refers to the expectation of economic costs incurred by the presence of these actors in a host country, particularly the expectation of actors' reliance on a host country's welfare system (Ana, 1999; Baker & McEnery,

Table 4. Regression of Sentiments on Frames.

	Dependent variable
	Sentiment
Agency	-0.242*** (0.033)
Economic Cost	-0.109* (0.053)
Permanence	-0.194*** (0.054)
Threat	-0.586*** (0.053)
Observations	60,184
Log likelihood	-100,934

* $p < .05$; ** $p < .01$; *** $p < .001$.

2005; Greenberg, 2000; Hardy, 2003; Santa Ana, 2002). Finally, actors have been portrayed as constituting a criminal threat to host societies (Bradimore & Bauder, 2011; Cohen, 2002; van Dijk, 1998).

Example comments representing each of these dimensions, and brief discussions on these, appear in Appendix 3. These new framing codes are defined by the following indicators, where “|” denotes the logical “or”:

$$\text{Agency} = \mathcal{I}(\text{Migrant} | \text{Immigrant})$$

$$\text{Economic Cost} = \mathcal{I}(\text{Refugee} | \text{Syrian} | \text{Asylum Seeker})$$

$$\text{Permanence} = \mathcal{I}\left(\begin{array}{l} \text{Refugee} | \text{Immigrant} | \\ \text{Syrian} | \text{Asylum Seeker} \end{array}\right)$$

$$\text{Threat} = \mathcal{I}(\text{Threat})$$

A comment harboring the Immigrant code (and labels therein) refers to actors whose reasons for crossing borders are unknown and perceived to be associated with a much higher degree of agency and potential permanent stay, whereas Refugee and Asylum Seeker imply a lower degree of agency, as does Syrian, all of which would be excluded from the Agency dimension. The Migrant code (and labels therein) not only harbor a high degree of agency but also can be associated with transience or less permanence in residency, which may be viewed with less apprehension in the eyes of commenters, and is consequently omitted from Permanence.

In Table 4, we use these four frames to predict the overall sentiment level of each comment, through an ordered logit regression, to answer RQ4. Naturally, all four frames contribute to negative sentiment for reasons already mentioned (i.e., the discussion of the labels under the umbrella codes are more negative than comments without labels). As expected, Threat impacts sentiment most negatively. However, Threat

Table 5. Topic Modeling of Positive Comments.

Topic	Wgt	Top words
Refugee crisis video (RC) (5 relevant [top-weighted] listed, $\mathcal{L} = -8.03$)		
Video commentary	0.45	Video great good love nice people guy channel job work
Refugee	0.21	People country live good europe refugee life syrian year place
Exclamatory	0.14	Good comment nice lmao read wow pretty lol hope point
Acceptance	0.14	People refugee country europe love muslim syrian accept nation american
Religious peace	0.08	Religion muslim islam christian human peace law culture sense friend
Migrant crisis video (MC) (4 relevant listed, $\mathcal{L} = -7.87$)		
Video commentary	0.49	Good great video stefan love wow brilliant hope people point
Islam and world	0.21	Europe people country muslim live world good islam middle east
Arab world/religion	0.06	Arab europe black white africa people world proud church west
Germany/immigration	0.06	State germany change russia immigrant free immigrate nation society open

\mathcal{L} indicates the average log-likelihood per token (i.e., word).

Table 6. Topic Modeling of Negative Comments.

Topic	Wgt	Top words
Refugee crisis video (RC) (6 relevant [top-weighted] listed, $\mathcal{L} = -8.05$)		
Middle East conflict	0.51	Refugee people country europe live syrian problem war syria european
Antipathy	0.38	Fucking fuck comment video shit idiot hate people bullshit stupid
Criminal	0.26	Rape crime muslim sweden refugee women europe commit immigrant year
Religious conflict	0.22	Muslim religion islam people kill christian culture hate law islamic
Racism	0.18	People fear fact hate point source racist argument white group
Terrorism/ISIS	0.14	Terrorist war attack isis syria kill middle east start group
Migrant crisis video (MC) (7 relevant listed, $\mathcal{L} = -8.14$)		
Middle East conflict	0.79	People country europe war refugee germany world syria middle hate
Islam/Rape	0.32	Rape muslim europe islam immigrant crime sweden women years migrant
Antipathy	0.32	Fucking fuck shit idiot racist cunt stop stupid watch video
Racism	0.16	White hate black people whites guilt race man make rac
Jewish/Nazi	0.12	Jew nazi poor media jewish society work plan pole anti
Criminal	0.09	Violence person street god rapist act police house small state
Middle East	0.07	Iran world saudi isi ffs invasion greece modern arabia spread

\mathcal{L} indicates the average log-likelihood per token (i.e., word).

aside, an ordering emerges among the remaining three in that Agency contributes most negatively to sentiment, followed by Permanence, and finally Cost. These coefficients also significantly differ from one another ($p < .001$). Discussants appear to be least sympathetic toward actors perceived as threats or having agency, while the potential framing of actors that might be perceived to incur economic costs to host countries is least provocative.

Topic Modeling Results

In Tables 5 and 6, we present the most prominent topics uncovered by the LDA topic modeling for the most positive comments of each video's discussion thread and their most negative comments, respectively. This selection considers the sum sentiment score as mentioned earlier in the Methods section, and key labels are boldfaced. In both Tables 5 and 6, the first column contains a descriptive label, an interpretation of the topic inferred from the words that are members of the topic. The second column shows the Weight measure,

indicating relative prominence of the topic in the corpus; lowly weighted topics are omitted from the analysis.

We note several similarities and differences between the negative and positive topics, as well as across the videos. The positive comments are far fewer and hence less varied in the MC thread, which is again unsurprising given the video's negative tone. Similarly, the MC thread is both negatively more varied and also more focused, with the highest weighted negative topic of "Middle East conflict." Commentary on the video or other comments appear in both positive and negative topics, but positive commentary is distinct in two topics for the RC thread (Video commentary and Exclamatory). Furthermore, more relevant positive topics such as "Peace" and "Acceptance" appear for RC.

Topics pertaining to religion also appear in both positive and negative comments, including the descriptive label of "muslim" and "islam." Certain labels such as "refugee," "syrian," and "muslim" feature in both positive and negative topics, while "immigrant" features in only the negative comments for the RC but in both positive and negative comments

for the MC, which is not entirely surprising given its relatively high position in Figure 1 and again indicative of counter-opinions to the MC video and its negative comments, as does the appearance of the positive “Islam” topic in MC. In sum, the topic modeling reveals overlap in the usage of some key labels in the topics inferred from the most positive and negative comments of the videos.

To further explore these overlaps in topics within each set of the most positive and negative comments of each video, we employ network portrayals of topics and their member words, as detailed in the methods section. In Appendix 1, Figures 2a, 2b, 3a, and 3b, we visualize the WW networks for the most (a) positive and (b) negative comments of each video. For these networks, we include the top 50 prominent topic words occurring in each topic. The network statistics of node size (n), edge count ($|E|$), graph density (d), and modularity (q) appear in the subcaptions of each network.¹²

For the RC networks, through visual inspection of the words that cross topics in both positive and negative networks, “people” is the most prominent and central in both RC networks and highly prominent in the positive MC network, and is thus a highly connective concept. This is not entirely surprising given the main topic of this article (the refugee/migrant crisis). Among the terms spanning positive topics, as seen in Figures 2a and 3a, we observe positive terms such as “good,” “accept,” “hope,” “love” as well as neutral terms such as “Europe[an],” “culture,” “Muslim,” “human,” “fact.” While some of these terms apply to topics relating to the video or other users’ comments, they also attest to a positive, humanistic perspective of the refugee crisis.

As seen in Figure 2b, some of these spanning words referring to groups of people also appear in the set of topic-crossing words for negative comments (such as “Europe” and “human”) as well as negative words (such as “afraid,” “hate,” “murder”), indicating that the antipathy-laden terminology pervades multiple topics of discussion. Furthermore, the extent of topic cross-over is higher for the negative topics than for the positive, as indicated by the relatively lower betweenness centrality scores (smaller sizes of the spanning nodes) and the lower modularity q statistic. That is, positivity employs distinct terms while the topics for negativity overlap far more and display less distinctiveness. Alternatively, one might argue that commenters find more negative and overlapping perspectives (and terminology) to the refugee/migrant crisis than they do positive ones. Finally, we observe that among the key labels, only a handful appear prominently among the top words in the topic models—namely, “refugee,” “immigrant,” “syrian,” and “muslim.” This is likely due to these terms’ usage being higher than the other key labels of the situation as seen in Table 2.

The MC networks exhibit some noticeable differences from the RC networks, as seen in Figure 3a and 3b. The prominence of “people” is muted, particularly in the negative topic network (see Figure 3b), possibly indicating less humanization in discussing those fleeing hardship. Furthermore, in the

negative topics, “people” is overshadowed by directly negative terms such as “violence,” “kill,” and “sh-t.” The topics are more partitioned given the lack of connectivity between the orange and blue clusters, with two other topics intervening as more central and prominent. Similarly, the negative topic network is also fragmented and, unsurprisingly, exhibits strongly negative terms (more so than RC), such as “kill,” “cancer,” “violence,” “sh-t,” appearing as words bridging topics and overshadowing the prominence of “people” which is connective in the other networks. Despite modularity’s indication that positive MC topics are less distinctive than negative ones (converse of RC), the presence of more prominent and central terms in the former mitigates this reversal and supports some distinctiveness found in positive topics.

In answering RQ3, these results reveal the extent of separation within the more positively laced and also the more negatively laced discussions. The topics, and therefore comments, harboring negative sentiments appear to exhibit higher co-mingling of terms and overlap of topics. Discussions involving positive comments display greater distinctiveness as well as more detailed descriptors of people groups. Still, the q statistics indicate more distinctiveness of negative topics in MC and positive topics in RC, suggesting that tonal framing of the stimulus itself (i.e., video) elicits some distinction in the portions of the discussion that is, sentiment-wise, consistent with the respective video’s tone.

Conclusion

Social media platforms, such as YouTube, only exist through the continual and growing participation of millions of users, and depend on individual and collective participation and creation of content. Social media responses to societal events, often times characterized by the relative anonymity of personal expression—particularly commenting on YouTube—can lead to empowered and uninhibited public opinion (Halpern & Gibbs, 2013; Hanson et al., 2010). As such, the use of labels to frame these recent events in Europe can have implications for the lives and safety of refugees; they can undermine public support, steer public opinion, and influence reactions to this crisis. Frames are never neutral. They define an issue, identify causes, make moral judgments, and shape proposed solutions (O’Neill et al., 2015). The significance of framing lies in the fact that it can affect both individuals and society at large. At the individual level, exposure to frames may result in altered attitudes, while at the societal level, frames can influence processes of political socialization and collective action (de Vreese, 2005).

Mostly studied in the context of the mass media, the use of labels as framing instruments has become an integral part of social media and the online world. Labels such as “refugee” and “migrant”—being employed for different purposes and evoking different connotations—become social categorization devices, not only demarcating “the population” from the “other,” but also distinguishing between those who are

deserving from those who are considered less-deserving and potentially a threat to be rejected (Foucault, Bertani, Fontana, Ewald, & Macey, 2003; Foucault, Senellart, Ewald, & Fontana, 2007). Furthermore, such lexical selectivity has been shown to distort public perceptions of refugees and migrants alike (Hier & Greenberg, 2002) and shape specific actions including marginalizing practices (Fairclough, 2000; O'Doherty & Lecouteur, 2007).

With this study, we aimed to provide a robust analysis of label use in social media surrounding the recent influx of displaced Middle-Eastern individuals, the emergent patterns of labeling, that can cause further disaffection and conflicts, and the sentiments associated with the different labels.

Our analysis of 46,313 comments posted to the sympathetic YouTube video "The European Refugee Crisis and Syria Explained" and 13,871 comments of the antipathetic "What Pisses Me Off About The European Migrant Crisis" showed moderate to heavily negative sentiment associated with the selected labels.

Through topic modeling, we identified the prevailing topics in the comment threads pertaining to more than those raised in the videos themselves, including other topics related to the refugee/migrant crisis. A network analysis of the words of each topic revealed extensive overlap in the usage of terms that constitute various discussions of the most positive and negative topics. Through this portrayal, we discover that the distinctiveness of topics aligns with the tone of the video. That is, the tone of the video induces more partitioning in those comments of similar sentiment. This particular finding, although unsurprising, points to the influence the content of a YouTube video has on the focus of user reactions expressed via comments and replies.

Our study revealed that while there is widespread usage of the various key labels in describing the refugee/migrant crisis and the affected individuals, discussion of the crisis centered on a smaller subset of these labels. Furthermore, the sentiments associated with labels displayed considerable variety in intensity and valence. So, while many of these labels can be argued to be virtually synonymous in a more general context, their framing and interpretation within the context of the crisis can vary considerably. Prominent labels were integrated into discussion topics found in the overall corpus of the studied comments. How these discussion topics manifest structurally is dependent on the sympathetic (or antipathetic) tone of the discussion. Negatively laced discussion of the refugee/migrant crisis centered on specific dimensions of racism, concerns or fears of crime, religion, and terrorist activity, while positive discussion highlighted peace, acceptance, and an open world.

Label Use and Perceived Agency, Economic Cost, Permanence, and Threat

As previous research has found that labels used to describe refugees and migrants are associated with characteristics or dimensions of agency, economic cost, permanence, and threat

of criminality (e.g., Baker & McEnery, 2005; Bradimore & Bauder, 2011; Dustmann et al., 2017; Van Dijk, 1988), we re-coded our labels into these four dimensions, according to the literature discussions. Through this analysis, we show how these dimensions impact the sentiments surrounding the labels. The re-coding presumed that most commenters harbor some degree of apprehension or antipathy toward foreigners but then this negative regard is mitigated when the extent of perceived agency is minimal. Here, the concept of perceived agency is employed to suggest the idea that such labels as "migrant" and "immigrant" carry an inherent meaning that these individuals have more freedom of choice and suffer from relatively less duress when deciding to leave their countries.

As such, Syrian refugees are a specific and perhaps the most sympathetic subgroup of the overall refugees, as envisioned in the minds of commenters, due to their dire situation, and corroborated by findings in the article. This is also consistent with findings from behavioral economics that reveal an increase in sympathy for specifically identified victims (e.g., Small & Loewenstein, 2003). While Refugee and Asylum Seeker imply a lower degree of agency, their motivations for crossing borders are less clear than those associated with the Syrian code.

When we extrapolated the presence of agency and permanence, as well as economic cost and threat, from the codes and test their prediction of sentiment, we found a distinct ordering in which—ignoring the obvious effect of threat—actors with perceived agency are most negatively attributed, while cost is significantly less important. Commenters are least sympathetic toward those perceived to have a choice when crossing borders. Perceived economic cost, surprisingly, appeared to elicit the least negativity, contrary to its emphasis in the literature (Ana, 1999; Baker & McEnery, 2005; Greenberg, 2000; Hardy, 2003; Santa Ana, 2002). This all suggests that antipathy is focused on those who choose to enter (a host country) and permanently reside, incurring costs that are not necessarily economic but perhaps social and cultural.

This four-dimensional model of label interpretation—that accounts for distinct frames—revealed important influential aspects of labels and frames that may shape online public opinion and alter attitudes toward those directly affected by the crisis. These aspects reframe responsibility and choice at the level of the individual, sorting those who are perceived to be deserving from those who are less-deserving (Holmes & Castañeda, 2016). The contribution of the four-dimensional model lies in its demonstration of how displaced people are situated within a discourse of risk, in which labels serve as categorization devices with clear implications for sentiment. These categorizations do not only influence the sentiments of public opinion, but they also depersonalize and objectify displaced individuals, which in turn contribute to the public's growing anxieties over the changing demographics and cultural diversity (Adeyanju & Neverson, 2007). Hence, we need to consider the broader, societal consequences of these categorizations.

The examination of taken-for-granted categorizations used in social media has the potential to uncover mechanisms of segregation, presenting “those different from us” as problematic and threatening (Hopkins et al., 1997). Thus, the discursive practices in social media, in particular, the use of the labels investigated in this study, could contribute toward the “legitimization of oppressive or marginalizing practices” toward those categorized as unwelcome to dominant segments of the host societies (O’Doherty & Lecouteur, 2007).

Limitations and Future Research

The data set analyzed in this study pertains to two, English language YouTube videos. It can be argued that the results presented in this study may not be representative of the overall, multilingual online discussions of the refugee crisis because many of the countries affected by the crisis are not anglophone. So, the framing of the crisis in these countries may differ. Therefore, a more comprehensive understanding of the overall perception of the refugee crisis in Europe would entail the inclusion of videos that employ the languages of those countries.

Social media textual data, such as the YouTube comments we investigated, contain a large number of malformed words, a blend of abbreviations, slang, colloquial expressions, and context specific terms (e.g., “looov,” “luv,” “gr8,” “lol,” etc.). While various data pre-processing methods are available, such informal text poses certain challenges for most text analysis methods. While we addressed some of the more thorny issues such as spelling errors and word usage (see Note 7), the impact of remaining issues—such as slang that is undetected by SentiStrength—on our analysis remains undetermined and worthy of investigation in the future.

The sentiment analysis method employed in this article uses a human-coded lexicon of words and phrases specifically built to work with online social data and recognizes some parts-of-speech in its scoring. 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, although its coverage is wide. This may pose problems when dealing with online textual data, where new expressions and jargon constantly emerge.

The significant results we presented prompt us to further explore our data. Our future plans include the analysis of salient words surrounding the labels, via a temporal or time-series analysis to expose the dynamics of label use, and alternative sentiment scores based on individual words rather than the most extreme sentiment-laden terms in a comment. Also, alternative text analytic methods such as semantic network analysis may reveal cross-associations between these labels that may appear in the comments, undetected by topic modeling networks. Finally, more precise analysis could consider the distinction between

comments and replies, examining the progression of label use within individual comment/reply threats.

The two videos selected for this study may also be considered a limiting factor to the generalizability of our findings. However, while it is safe to say that the opposing positions of just these two videos may not necessarily be completely representative of YouTube users (and their opinions) in general and could appeal to specific audience segments, the videos were the two most popular on the topic of the migrant/refugee crisis at the time of our data collection. These two videos, then, would have appeared at the top of any YouTube search for any visitor using the strings “refugee crisis” and/or “migrant crisis.” Given YouTube’s vast audience—over 30 million visitors per day with eight out of ten 18- to 49-year-olds watching videos on YouTube in the average month (Statista.com, 2018)—we can argue that the reach and visibility of these videos are not limited to the specific audiences of the videos’ authors and that the comments analyzed in this article had at least the potential to reach, influence, trigger responses from, and be representative of, a broader audience, especially considering earlier findings of YouTube comments’ aligning with public opinion (e.g., Mejova & Srinivasan, 2012) and their being more honest than those of other platforms (Halpern & Gibbs, 2013; Hanson et al., 2010).

Concluding Remarks

As social media becomes more prevalent, incurring higher levels of participation, and creation of content, studies of online opinions and discussions, such as this article, become increasingly valuable by offering insights into the nature and direction of focal discussion themes and public sentiment surrounding those themes. Still, the nature of these discussions and expressions of opinion may be strongly dependent on the characteristics of the platforms in which they occur, such as the level of anonymity afforded in the interactions among the users. In the case of the refugee crisis theme on YouTube, studies like ours, presenting a comprehensive overview of online opinions and sentiments related to these recent events, contribute toward the larger aim of creating frameworks capable of explaining online public opinion and affect.

In this work, we have not analyzed these frames as “all-powerful” but rather as constituting and developing through public debate and grassroots discourse, in the ever-present contest over labels and their meanings (Kallius, Monterescu, & Rajaram, 2016). This perspective has motivated us to question the discursive framing of labels surrounding the refugee/migrant crisis and examine how their use might spur further expression or evoke exclusion.

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Notes


1. The URL for the video is <https://www.youtube.com/watch?v=RvOnXh3NN9w>
2. The video can be viewed here <https://www.youtube.com/watch?v=cCOLcMqdpIs>
3. Stefan Molyneux published a number of other, less popular, negative videos on the topic of the refugee crisis: "Why Europe owes migrants nothing," "The Death of Germany—European Migrant Crisis," "What Pisses Me Off About The German Rape Attacks," "The Truth About Immigration and Welfare," and so on.
4. The 13,871 comments included in our corpus are those comments posted during the first 389 days from the publishing of the video. Because the comments of this second video have been collected almost 1 year after the first one (on 15 October 2017), we use the 389 days range to ensure alignment across our two videos.
5. While removal of punctuation consequently removes emoticons, less than 1.5% of comments contained any emoticon, so we feel their omission does not significantly impact the results. However, future work on this topic will consider inclusion of emoticons.
6. While there is some debate as to the utility of stemmers to topic modeling (Schofield & Mimno, 2016), we employed the Krovetz stemmer which Schofield and Mimno found to incur the least degradation, and in some cases improvements, according to their measures. Furthermore, for the purposes of this article, we were less interested in the exact semantic contexts distinguishing singular and plural forms of key labels (e.g., "refugee" vs. "refugees") and considered them to fall under common conceptualizations (e.g., just "refugee").
7. As social media comments are typically informally written, they often contain language errors, of which the most impactful ones to our analyses are spelling errors and incorrect word usage in mentioning the key labels. To address these, we manually identified incorrect bigrams and unigrams and constructed a codebook to map them on to the correct terminology. For example, "refuges crisis" was mapped to "refugee crisis." In addition, we expanded all verb contractions such that noise word deletion would be more effective. And finally, social media comments into textual form often contain HTML tags representing Unicode punctuation (e.g., "'" for an apostrophe), that also required re-mapping.
8. In addition to the lexicon-based sentiment identification, SentiStrength also assigns sentiment to emoticons based on a list with human-assigned sentiment scores.
9. The initial SentiStrength scores of -1 to -5 for negativity and +1 to +5 for positivity were recoded into the 0 to 4 range in which higher numbers indicate more intense sentiment, and -1 and +1 represent neutrality in the software.
10. While the label "asylum seeker" can often be synonymous with "refugee," it can also connote other kinds of asylum seekers (e.g., political asylum seekers), so we do not place it under the "Refugee" code. However, given the importance of "asylum seeker," we include it as a separate code in the

regression models and find its independent and significant prediction, supporting our choice of excluding it from the "Refugee" code.

11. We explain its exclusion from the "Refugee" code in Note 10.
12. The graph density and modularity statistics range from 0.0 to 1.0. Higher density indicates higher proportion of edge counts over the count of all possible edges, while higher modularity indicates distinct communities or clusters. The network sizes n are not strictly 50 times the number of topics as many words span multiple topics.

ORCID iDs

Ju-Sung Lee  <https://orcid.org/0000-0002-4158-2700>

Adina Nerghes  <https://orcid.org/0000-0002-8483-4357>

References

- Adeyanju, C. T., & Neverson, N. (2007). "There will be a next time": Media discourse about an "apocalyptic" vision of immigration, racial diversity, and health risks. *Canadian Ethnic Studies Journal*, 39(7/2), 79-105.
- Ana, O. S. (1999). "Like an animal I was treated": Anti-immigrant metaphor in US public discourse. *Discourse & Society*, 10, 191-224.
- Anstead, N., & O'Loughlin, B. (2015). Social media analysis and public opinion: The 2010 UK general election. *Journal of Computer-Mediated Communication*, 20, 204-220.
- Arun, R., Suresh, V., Madhavan, C. E. V., & Murthy, M. N. N. (2010). On finding the natural number of topics with latent Dirichlet allocation: Some observations. In M. J. Zaki, J. X. Yu, B. Ravindran, & V. Pudi (Eds.), *Advances in knowledge discovery and data mining* (pp. 391-402). Heidelberg, Germany: Springer.
- Augoustinos, M. (2001). Social categorization: Towards theoretical integration. In K. Deaux & G. Philogene (Eds.), *Representations of the social* (pp. 201-216). Oxford, UK: Blackwell Publishers.
- Augoustinos, M., & Quinn, C. J. (2003). Social categorization and attitudinal evaluations: Illegal immigrants, refugees, or asylum seekers? *New Review of Social Psychology*, 2, 29-37.
- Baker, P., & McEnery, T. (2005). A corpus-based approach to discourses of refugees and asylum seekers in UN and newspaper texts. *Journal of Language and Politics*, 4, 197-226.
- Bastian, M., Heymann, S., & Jacomy, M. (2009, May 16-20). *Gephi: An open source software for exploring and manipulating networks*. In N. Glance & M. Hurst (Eds.), International association for the advancement of artificial intelligence (AAAI) conference on weblogs and social media. Menlo Park, CA: AAAI.
- Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, 3, 993-1022.
- Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008(10), 1-12.
- boyd, d., & Crawford, K. (2012). Critical questions for big data. *Information, Communication and Society*, 15, 662-679.
- Brader, T., Valentino, N. A., & Suhay, E. (2008). What triggers public opposition to immigration? Anxiety, group cues, and immigration threat. *American Journal of Political Science*, 52, 959-978.

- Bradimore, A., & Bauder, H. (2011). Mystery ships and risky boat people: Tamil refugee migration in the newsprint media. *Canadian Journal of Communication*, 36, 637-661.
- Brewer, P. R. (2001). Value words and lizard brains: Do citizens deliberate about appeals to their core values? *Political Psychology*, 22, 45-64.
- Cacciatore, M. A., Scheufele, D. A., & Iyengar, S. (2016). The end of framing as we know it . . . and the future of media effects. *Mass Communication and Society*, 19, 7-23.
- Canali, C., Colajanni, M., & Lancellotti, R. (2010, March 15-19). Characteristics and evolution of content popularity and user relations in social networks. In S. Chessa (Ed.), *IEEE Symposium on 2010 Computers and Communications (ISCC)* (pp. 750-756). Riccione, Italy. Piscataway, NJ: IEEE.
- Canoy, M., Beutin, R., Horvath, A., Hubert, A., Lerais, F., & Sochacki, M. (2006). *Migration and public perception* (Technical report). Luxembourg City, Luxembourg: Bureau of European Policy Advisers (BEPA), European Commission.
- Cao, J., Xia, T., Li, J., Zhang, Y., & Tang, S. (2009). A density-based method for adaptive LDA model selection. *Neurocomputing*, 72, 1775-1781.
- Chatzopoulou, G., Sheng, C., & Faloutsos, M. (2010, March 15-19). A first step towards understanding popularity in YouTube. In G. Mandyam (Ed.), *INFOCOM IEEE Conference on Computer Communications Workshops, 2010* (pp. 1-6). San Diego, CA. Piscataway, NJ: IEEE.
- Chong, D., & Druckman, J. N. (2007). Framing theory. *Annual Review of Political Science*, 10, 103-126.
- Cohen, S. (2002). *Folk devils and moral panics: The creation of the mods and rockers* (3rd ed.). London, England: Routledge.
- Darling, J. (2014). Asylum and the post-political: Domopolitics, depoliticisation and acts of citizenship. *Antipode*, 46, 72-91.
- Deveaud, R., SanJuan, É., & Bellot, P. (2014). Accurate and effective latent concept modeling for ad hoc information retrieval. *Document Numérique*, 17, 61-84.
- de Vreese, C. H. (2005). News framing: Theory and typology. *Information Design Journal & Document Design*, 13, 51-62.
- Druckman, J. N. (2011). What's it all about? Framing in political science. In G. Keren (Ed.), *Perspectives on framing* (pp. 279-302). New York, NY: Psychology Press.
- Dustmann, C., Fasani, F., Frattini, T., Minale, L., & Schönberg, U. (2017). On the economics and politics of refugee migration. *Economic Policy*, 32, 497-550.
- Entman, R. M. (1993). Framing: Toward clarification of a fractured paradigm. *Journal of Communication*, 43(4), 50-58. doi:10.1111/j.1460-2466.1993.tb01304.x
- European Social Survey European Research Infrastructure Consortium (ESS ERIC). (2017). *Attitudes towards immigration in Europe: Myths and realities* (Technical report). Migration Policy Group, European Parliament. London, UK: City, University of London.
- Fairclough, N. (2000). *New labour, new language?* London, England: Routledge.
- Foucault, M., Bertani, M., Fontana, A., Ewald, F., & Macey, D. (2003). "Society must be defended": *Lectures at the Collège de France, 1975-1976* (Lectures at the Collège de France). New York, NY: Picador Press.
- Foucault, M., Senellart, M., Ewald, F., & Fontana, A. (2007). *Security, territory, population* (Lectures at the Collège de France). New York, NY: Palgrave Macmillan.
- Gamson, W. A., & Wolfsfeld, G. (1993). Movements and media as interacting systems. *The ANNALS of the American Academy of Political and Social Science*, 528, 114-125.
- Gill, P., Arlitt, M., Li, Z., & Mahanti, A. (2007, October 23-26). YouTube traffic characterization: A view from the edge. In C. Dovrolis & M. Roughan (Eds.), *Proceedings of the 7th ACM SIGCOMM conference on Internet measurement* (pp. 15-28). San Diego, CA. New York, NY: Association for Computing Machinery.
- Goffman, E. (1974). *Frame analysis: An essay on the organization of experience*. New York, NY: Harvard University Press.
- Greenberg, J. (2000). Opinion discourse and Canadian newspapers: The case of the Chinese" boat people." *Canadian Journal of Communication*, 25(4), 517-538.
- Griffiths, T. L., & Steyvers, M. (2002, August 7-10). A probabilistic approach to semantic representation. In W. Gray & C. Shunn (Eds.), *Proceedings of the 24th Annual Conference of the Cognitive Science Society* (pp. 381-386). VA: George Mason University.
- Griffiths, T. L., & Steyvers, M. (2003). Prediction and semantic association. In S. Becker, S. Thrun, & K. Obermayer (Eds.), *Neural information processing systems 15* (pp. 11-18). Cambridge, MA: MIT Press.
- Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences*, 101(Suppl. 1), 5228-5235.
- Hallahan, K. (1999). Seven models of framing: Implications for public relations. *Journal of Public Relations Research*, 11, 205-242.
- Halpern, D., & Gibbs, J. (2013). Social media as a catalyst for online deliberation? Exploring the affordances of Facebook and YouTube for political expression. *Computers in Human Behavior*, 29, 1159-1168.
- Hanson, G., Haridakis, P. M., Cunningham, A. W., Sharma, R., & Ponder, J. D. (2010). The 2008 presidential campaign: Political cynicism in the age of Facebook, MySpace, and YouTube. *Mass Communication and Society*, 13, 584-607.
- Hardy, V. K. (2003). *Metaphoric myth in the representation of Hispanics* (Doctoral dissertation). Georgetown University, Washington, DC.
- Haynes, A., Devereux, E., & Breen, M. (2008). Public exercises in othering: Irish print media coverage of asylum seekers and refugees. In B. Farago & S. M. (Eds.), *Facing the other: Interdisciplinary studies on race, gender and social justice in Ireland* (pp. 162-181). Newcastle, UK: Cambridge Scholars Press.
- Heckner, M., & Wolff, C. (2009). Towards social information seeking and interaction on the web. In R. Kuhlen (Ed.), *Information: Droge, ware oder commons? Wertschöpfungs- und Transformationsprozesse auf den Informationsmärkten* (Vol. 50, pp. 235-241). Boizenburg, Germany: vwh Verlag Werner Hülsbusch.
- Hier, S. P., & Greenberg, J. L. (2002). Constructing a discursive crisis: Risk, problematization and illegal Chinese in Canada. *Ethnic and Racial Studies*, 25, 490-513.
- Hofmann, T. (1999). Probabilistic latent semantic indexing. In F. Gey, M. Hearst, & R. Tong (Eds.), *Proceedings of the 22nd annual international ACM SIGIR conference on research and development in information retrieval* (pp. 50-57). Berkeley, CA: Association for Computing Machinery.
- Hofmann, T. (2001). Unsupervised learning by probabilistic latent semantic analysis. *Machine Learning*, 42, 177-196.

- Holmes, S. M., & Castañeda, H. (2016). Representing the "European refugee crisis" in Germany and beyond: Deservingness and difference, life and death. *American Ethnologist*, 43(1), 12-24.
- Hopkins, N., Reicher, S., & Levine, M. (1997). On the parallels between social cognition and the new racism. *British Journal of Social Psychology*, 36, 305-329.
- Horsti, K. (2007). Asylum seekers in the news: Frames of illegality and control. *Observatorio Journal*, 1, 145-161.
- Iyengar, S. (1987). Television news and citizens' explanations of national affairs. *American Political Science Review*, 81, 815-831. doi:10.2307/1962678
- Jones, G. M., & Schieffelin, B. B. (2009). Talking text and talking back: "My BFF Jill" from boob tube to YouTube. *Journal of Computer-Mediated Communication*, 14, 1050-1079.
- Kahneman, D., & Tversky, A. (1984). Choices, values, and frames. *American Psychologist*, 39, 341-350.
- Kallius, A., Monterescu, D., & Rajaram, P. K. (2016). Immobilizing mobility: Border ethnography, illiberal democracy, and the politics of the refugee crisis in Hungary. *American Ethnologist*, 43, 25-37.
- Kempadoo, K. (2005). Victims and agents of crime: The new crusade against trafficking. In J. Sudbury (Ed.), *Global lockdown: Race, gender, and the prison-industrial complex* (pp. 35-55). New York, NY: Routledge.
- Kirk, R., & Schill, D. (2011). A digital agora: Citizen participation in the 2008 presidential debates. *American Behavioral Scientist*, 55, 325-347.
- Knoll, B. R., Redlawsk, D. P., & Sanborn, H. (2011). Framing labels and immigration policy attitudes in the Iowa caucuses: "Trying to out-tancredo Tancredo." *Political Behavior*, 33, 433-454.
- Kousha, K., Thelwall, M., & Abdoli, M. (2012). The role of online videos in research communication: A content analysis of YouTube videos cited in academic publications. *Journal of the American Society for Information Science and Technology*, 63, 1710-1727.
- Lange, P. G. (2007a, March 28-31). Commenting on comments: Investigating responses to antagonism on YouTube. In N. Romero-Daza, D. Himmelgreen, & M. Angrosino (Eds.), *Society for applied anthropology conference* (Vol. 31, p. 2007). Tampa, FL: Society for Applied Anthropology.
- Lange, P. G. (2007b). Publicly private and privately public: Social networking on YouTube. *Journal of Computer-Mediated Communication*, 13, 361-380.
- Lee, J.-S., & Nerghes, A. (2017, July 28-30). Labels and sentiment in social media: On the role of perceived agency in online discussions of the refugee crisis. In A. Gruzdev & B. Hogan (Eds.), *Proceedings of the 8th International Conference on Social Media & Society* (pp. 1-10, Article no.14). Toronto, Ontario, Canada: ACM.
- Lillie, S. E. (2008). Diffusion of innovation in the age of YouTube. *American Journal of Preventive Medicine*, 34, 267.
- Madden, A., Ruthven, I., & McMenemy, D. (2013). A classification scheme for content analyses of YouTube video comments. *Journal of Documentation*, 69, 693-714.
- Mäkinen, M., & Wangu Kuira, M. (2008). Social media and post-election crisis in Kenya. *The International Journal of Press/Politics*, 13, 328-335.
- McCallum, A. K. (2002). *MALLET: A machine learning for language toolkit*. Available from <http://mallet.cs.umass.edu>
- Mejova, Y., & Srinivasan, P. (2012, June 22-24). Political speech in social media streams: YouTube comments and Twitter posts. In M. Macy & W. Nejdl (Eds.), *Proceedings of the 4th Annual ACM Web Science Conference, WebSci '12* (pp. 205-208). Evanston, IL: ACM.
- Milliken, M. C., & O'Donnell, S. (2008). User-generated online video: The next public sphere? In W. McIver & S. O'Donnell (Eds.), *Technology and society, 2008 ISTAS 2008* (pp. 1-3). June 7-9, 2010. New South Wales, Australia: IEEE
- Naimou, A. (2016). Double vision: Refugee crises and the afterimages of endless war. *College Literature*, 43, 226-233.
- Nikita, M. (2016). *ldatuning: Tuning of the Latent Dirichlet allocation models parameters* (R package version 0.2.0). Retrieved from <https://CRAN.R-project.org/package=ldatuning>
- O'Connor, B., Balasubramanyam, R., Routledge, B. R., & Smith, N. A. (2010). From tweets to polls: Linking text sentiment to public opinion time series. *ICWSM*, 11(122-129), 1-2.
- O'Doherty, K., & Lecouteur, A. (2007). "Asylum seekers," "boat people" and "illegal immigrants": Social categorisation in the media. *Australian Journal of Psychology*, 59, 1-12.
- O'Neill, S., Williams, H. T. P., Kurz, T., Wiersma, B., & Boykoff, M. (2015). Dominant frames in legacy and social media coverage of the IPCC fifth assessment report. *Nature Climate Change*, 5, 380-385.
- Pan, Z., & Kosicki, G. M. (1993). Framing analysis: An approach to news discourse. *Political Communication*, 10(1), 55-75.
- Paolillo, J. C. (2008, January 7-10). Structure and network in the YouTube core. In R. Sprague Jr. (Ed.), *Proceedings of the 41st Annual HICSS conference* (pp. 156-156). Waikoloa, HI: IEEE Computer Society.
- Papacharissi, Z. (2002). The virtual sphere: The internet as a public sphere. *New Media & Society*, 4(1), 9-27.
- Porter, A. J., & Hellsten, I. (2014). Investigating participatory dynamics through social media using a multideterminant "frame" approach: The case of Climategate on YouTube. *Journal of Computer-Mediated Communication*, 19, 1024-1041.
- Reilly, P. (2014). *Battle of Stokes Croft on YouTube: The ethical challenges associated with the study of online comments*. Retrieved from <https://www.psa.ac.uk/insight-plus/blog/battle-stokes-croft-youtube-ethical-challenges-associated-study-online-comments>
- Rieder, B. (2015). *YouTube data tools*. Retrieved from <https://tools.digitalmethods.net/netvizz/youtube/>
- Roggeband, C., & Verloo, M. (2007). Dutch women are liberated, migrant women are a problem: The evolution of policy frames on gender and migration in the Netherlands, 1995-2005. *Social Policy & Administration*, 41, 271-288.
- Roggeband, C., & Vliegthart, R. (2007). Divergent framing: The public debate on migration in the Dutch parliament and media, 1995-2004. *West European Politics*, 30, 524-548.
- Rohan, M. J. (2000). A rose by any name? The values construct. *Personality and Social Psychology Review*, 4, 255-277.
- Santa Ana, O. (2002). *Brown tide rising: Metaphors of Latinos in contemporary American public discourse*. Austin: University of Texas Press.
- Schofield, A., & Mimno, D. (2016). Comparing apples to apple: The effects of stemmers on topic models. *Transactions of the Association for Computational Linguistics*, 4, 287-300.
- Schultes, P., Dorner, V., & Lehner, F. (2013). Leave a comment! An in-depth analysis of user comments on YouTube. *Wirtschaftsinformatik*, 42, 659-673.
- Siersdorfer, S., Chelaru, S., Nejdl, W., & San Pedro, J. (2010, April 26-30). How useful are your comments? Analyzing and

- predicting YouTube comments and comment ratings. In M. Rappa & P. Jones (Eds.), *Proceedings of the 19th international conference on World Wide Web* (pp. 891-900). Raleigh, NC: Association for Computing Machinery.
- Small, D., & Loewenstein, G. (2003). Helping a victim or helping THE victim: Altruism and identifiability. *Journal of Risk and Uncertainty*, 26, 5-16.
- Smith, A. N., Fischer, E., & Yongjian, C. (2012). How does brand-related user-generated content differ across YouTube, Facebook, and Twitter? *Journal of Interactive Marketing*, 26, 102-113.
- Sobkowicz, P., Kaschesky, M., & Bouchard, G. (2012). Opinion mining in social media: Modeling, simulating, and forecasting political opinions in the web. *Government Information Quarterly*, 29, 470-479.
- Socialbakers.com (2018). *YouTube statistics directory*. Retrieved from <https://www.socialbakers.com/statistics/youtube/>
- Statista.com (2018, April). Most famous social network sites worldwide as of January 2018, ranked by number of active users (in millions). Retrieved from <https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/>
- Thelwall, M. (2013). Heart and soul: Sentiment strength detection in the social web with SentiStrength. In J. Holyst (Ed.), *Proceedings of the CyberEmotions* (pp. 1-14). Basel, Switzerland: Springer International Publishing Switzerland.
- Thelwall, M., Buckley, K., Paltoglou, G., Cai, D., & Kappas, A. (2010). Sentiment strength detection in short informal text. *Journal of the American Society for Information Science and Technology*, 61, 2544-2558.
- Townsend, L., & Wallace, C. (2016). *Social media research: A guide to ethics*. Aberdeen, Scotland: University of Aberdeen.
- Tversky, A., & Kahneman, D. (1985). The framing of decisions and the psychology of choice. In V. T. Covello, J. L. Mumpower, P. J. M. Stallen, & V. R. R. Uppuluri (Eds.), *Environmental impact assessment, technology assessment, and risk analysis* (pp. 107-129). Berlin, Germany: Springer.
- van Dijk, T. A. (1988). Semantics of a Press Panic: The Tamil "invasion." *European Journal of Communication*, 3, 167-187.
- van Dijk, T. A. (1998). What is political discourse analysis? In J. Blommaert & C. Bulcaen (Eds.), *Political linguistics* (pp. 11-52). Amsterdam, The Netherlands: Benjamins.
- Walther, J. B., DeAndrea, D., Kim, J., & Anthony, J. C. (2010). The influence of online comments on perceptions of anti-marijuana public service announcements on YouTube. *Human Communication Research*, 36, 469-492.
- Wikipedia. (2015). *European migrant crisis*. Retrieved from https://en.wikipedia.org/wiki/European_migrant_crisis
- Zeng, D., Chen, H., Lusch, R., & Li, S.-H. (2010). Social media analytics and intelligence. *IEEE Intelligent Systems*, 25(6), 13-16.

Author Biographies

Ju-Sung Lee (PhD, Carnegie Mellon University) is an assistant professor in the Department of Media and Communication at Erasmus University Rotterdam. His research interests lie at the nexus of social, communication, and semantic networks.

Adina Nerghes (PhD, Vrije Universiteit Amsterdam) is a postdoctoral researcher in the DHLab at the KNAW Humanities Cluster. Her research focuses on language use in various social contexts and emerging social structures.

Networks of Topic Members

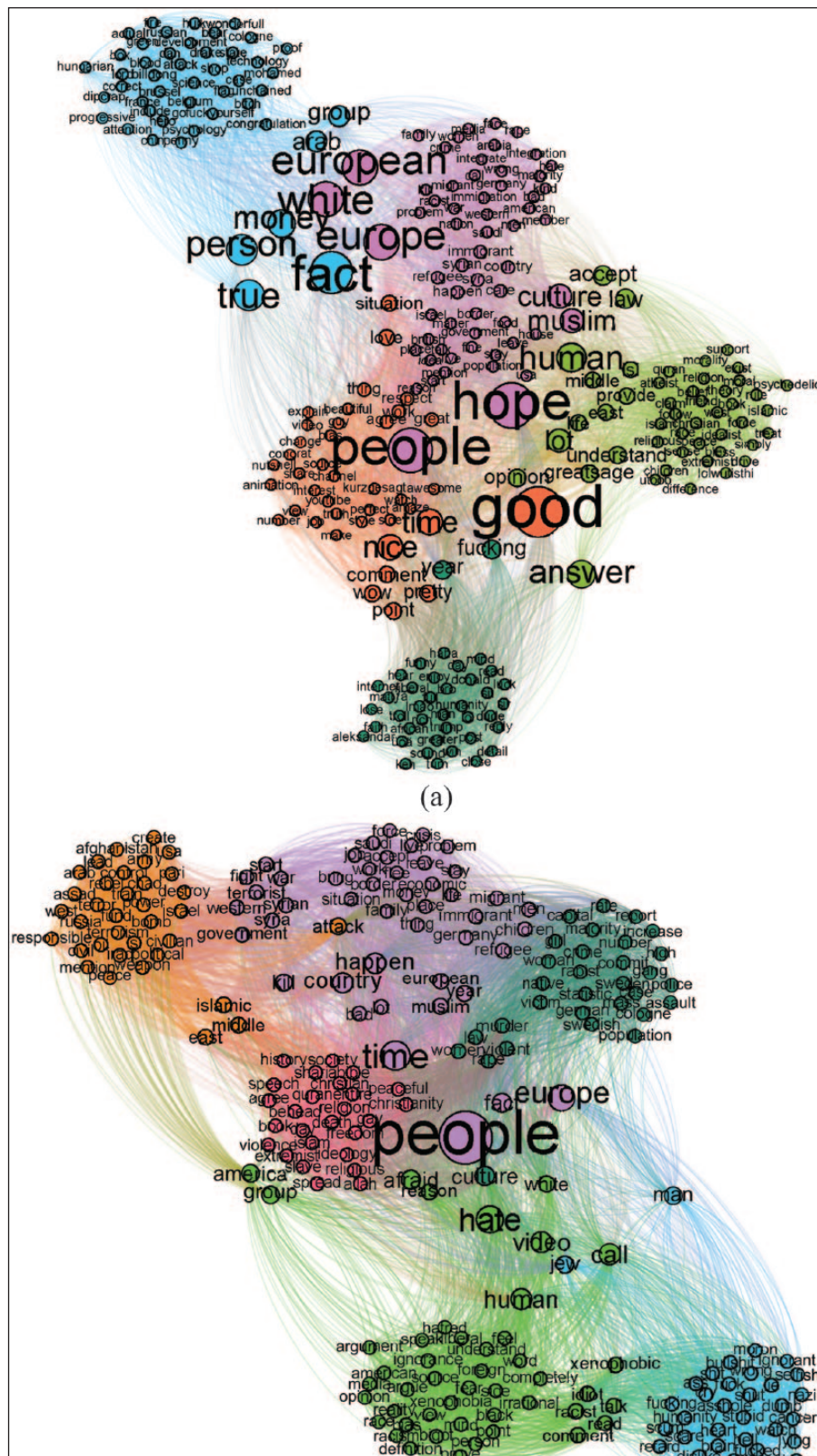


Figure 2. Word–word affiliation for refugee crisis (RC) video (for all positive and negative topics): (a) Positive topics ($n=222$, $|E|=6,892$, $d=281$, $q=502$) and (b) Negative topics ($n=235$, $|E|=7,062$, $d=257$, $q=411$).



Figure 3. Word–word affiliation for migrant crisis (MC) video (for all positive and negative topics): (a) Positive topics ($n = 167$, $|E| = 4,796$, $d = 346$, $q = 453$) and (b) Negative topics ($n = 287$, $|E| = 8,428$, $d = 205$, $q = 509$).

Appendix 2

Most Frequent Unigrams

Table 7. Top Frequent Unigrams.

	RC		MC	
	%	Word	%	Word
1	2.02	People	1.49	People
2	1.72	Refugee	1.31	Europe
3	1.46	Country	1.12	Country
4	0.99	Muslim	0.77	Like
5	0.80	Europe	0.62	Muslim
6	0.66	Video	0.59	Refugee
7	0.53	War	0.57	Germany
8	0.51	Help	0.51	World
9	0.50	Live	0.50	War
10	0.47	Syrian	0.46	Want
11	0.41	Problem	0.44	Think
12	0.38	Syria	0.40	Know
13	0.36	European	0.40	White
14	0.36	Good	0.40	Syria
15	0.35	Well	0.35	Islam
16	0.35	Fact	0.34	America
17	0.35	Rape	0.33	Immigrant
18	0.33	Religion	0.33	Right
19	0.32	Immigrant	0.32	Say
20	0.32	Germany	0.32	Culture

RC: refugee crisis; MC: migrant crisis.

Appendix 3

Examples of Comments for the Four Dimensions

In this appendix, an example comment linking label use to each of the four dimensions of Agency, Economic Cost, Permanence, and Threat are provided. For anonymity purposes, we have omitted each comment's author's name.

Agency. "Most of the *immigrants* aren't even from Syria, they're just pretending to be so they can get a free handout from Europe"

The above comment states that displaced people, here labeled as immigrants, are not from a war torn zone (Syria). Hence, the user posting this comment is attributing agency to these "immigrants" by implying they are leaving their countries of origin of their own free will and for some type of gain ("free handout"). Thus, this quote's use of "immigrant" would also associate the term to the Economic Cost dimension.

Economic Cost

Refugees don't travel through safe countries to get to the countries with the most generous welfare systems (Germany & Sweden). These people are economical migrants, not refugees.

The comment we show above is a perfect example of the Economic Cost dimension. The author clearly states that

refugees coming into Europe are economic(al) migrants trying to reach welfare states, thus associating the Refugee code to this dimension.

Permanence

I honestly think *asylum seekers* should get easy access to Europe, though it should only be considered on a temporary basis until it's safe for them to return to their own country . . .

The Permanence dimension, or rather the aversion toward a more permanent residency status of displaced people—labeled here as "asylum seekers"—is expressed by this user by suggesting that access to Europe should be granted on a temporary basis.

Threat

These mostly muslim ILLEGAL IMMIGRANTS should be returned to their country of origin. How many criminals, rapists and worse TERRORISTS are among these swarms of completely undocumented illegals. What will the left wing do gooders say when the disgusting muslim terrorist bombs start exploding in our Citys again?

The last quote we present in this appendix speaks to the Threat dimension. As seen in the above comment, the author

uses very strong language and several labels—such as illegal, criminals, and rapists—to express a very vehement opinion on the displaced people coming into Europe.

Appendix 4

Topic Modeling Diagnostics

In order to determine the ideal number of topics for our topic modeling of the positive and negative comments subsets (sub-corpora) of each of the refugee crisis (RC) and migrant crisis (MC) videos, we employ several diagnostics. The first metrics include those implemented in the *ldatuning* R package (Nikita, 2016), proposed by Griffiths and Steyvers (2004); Cao, Xia, Li, Zhang and Tang (2009); Arun, Suresh, Madhavan, & Murthy, (2010); and Deveaud, SanJuan, and Bellot (2014). Not all measures are informative as some are

observed to monotonically decrease or increase; hence, only those non-monotonic patterns (with non-trivial minima and maxima) are reported. These measures are normalized by their empirical ranges to the $[0,1]$ interval.

The second metric is drawn from 10-fold cross-validation in which a test set of 1/10th of each sub-corpus is predicted using a training set, and the performance of the prediction is captured by the perplexity measure. All metrics were tested using topic numbers between 2 and 50, but for presentation purposes, metrics for up to 25 topics in Figures 4 and 5 are shown; the trends do not exhibit non-monotonicity beyond 25 topics.

The figures reveal that our choice of eight topics lies at or near to the optimal number of topics. An investigation into the actual topic memberships for models with slightly more than eight topics, for each of the sub-corpora, reveals neither significant qualitative differences in topic memberships nor additional prominent topics.

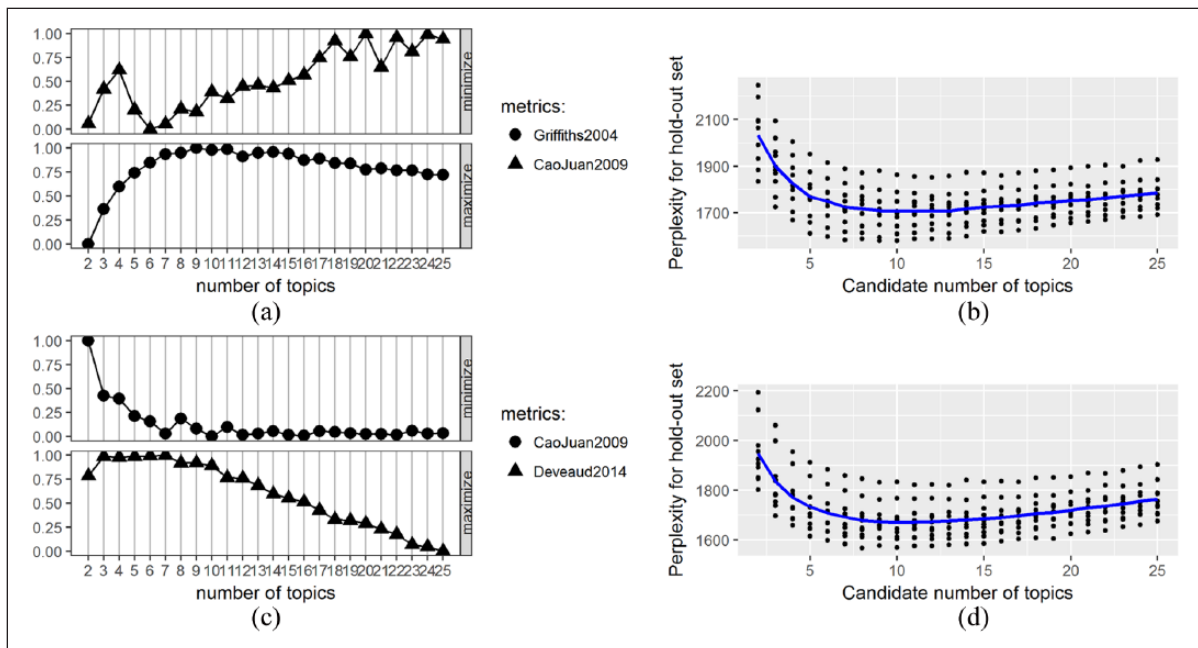


Figure 4. Topic modeling diagnostics for RC comments: (a) Metrics for RC positive comments, (b) cross-validation for RC positive comments, (c) metrics for RC negative comments, and (d) cross-validation for RC negative comments. RC: refugee crisis.

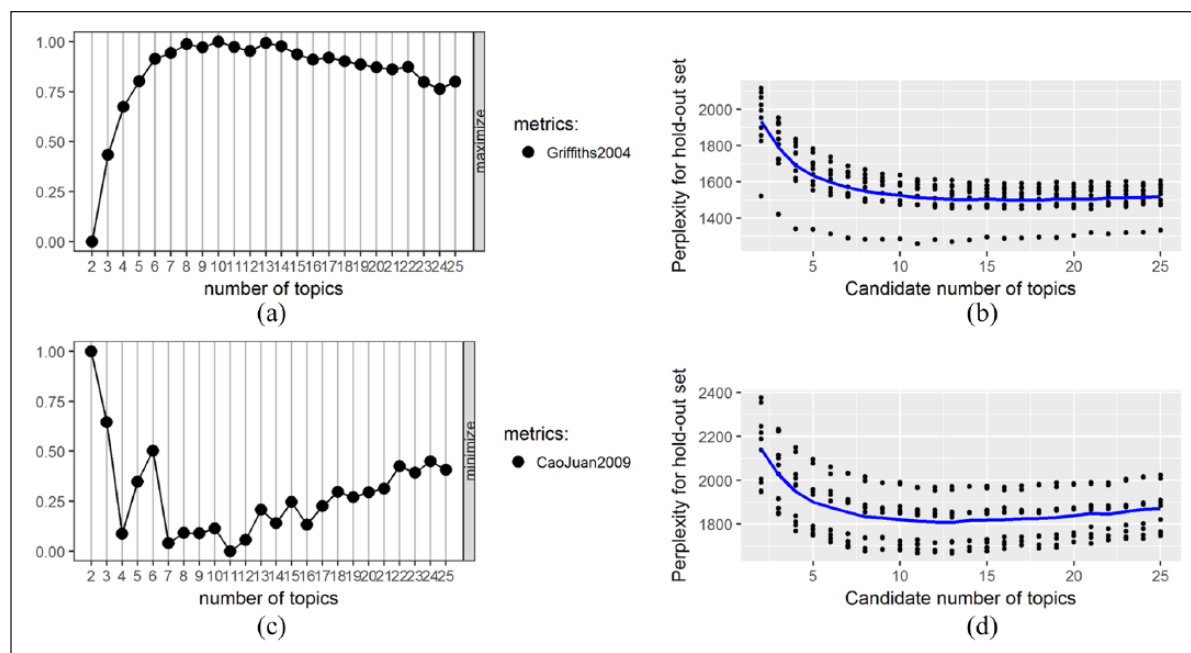


Figure 5. Topic modeling diagnostics for MC comments: (a) Metrics for MC positive comments, (b) cross-validation for MC positive comments, (c) metrics for MC negative comments, and (d) cross-validation for MC negative comments. MC: migrant crisis.