

THE SOCIAL PSYCHOLOGY OF SOCIAL MEDIA REACTIONS TO TERRORISM

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Thesis Prepared for the Degree of

MASTER OF SCIENCE

UNIVERSITY OF NORTH TEXAS

December 2016

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Demirhan, Emirhan. *The Social Psychology of Social Media Reactions to Terrorism*.

Master of Science (Sociology), December 2016, 52 pp., 9 tables, 3 figures, references, 84 titles.

Columnists and social media users commonly stated that terrorist attacks resonate differently in the world and they speculated on some potential reasons such as familiarity, number of victims, and the difference in expectations of a country to be a stage for a terrorist attack to explain this difference. An academic perspective, more specifically a sociological one, is needed to bring light to this debate. In this study, I aimed to understand the discourse after terrorist attacks and to find out if there is a difference between reactions to terrorist attack based on where they happened. This paper embraces a text mining approach to uncover what topics are discussed after four cases of terrorist attacks and to reveal if there is a discrepancy in reactions towards terrorist attacks based on the country they happened. The study consists of two parts. In the first part, the determinants of the public interest and support and how public interest differentiates between different cases of terror attacks is explored. In the second part, topic sentiment analysis is conducted to reveal the nature of the discourse on terrorism. Using the insights from social identity theory, realistic conflict theory and integrated threat theory, I argued that social group categorization in the context of terrorism takes place in a dichotomous manner as Western and Non-Western. This argument, social self-identities being based on 'West vs. the Rest' mentality in the context of terrorism, is supported by the statistical evidence and the topic model. Theoretical and practical implications are discussed.

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ACKNOWLEDGEMENTS

I would like to express my special appreciation to my committee chair Dr. Gabriel Ignatow, co-chair Nick Evangelopoulos, and member Dr. Michael F. Thompson for their extensive guidance and support. I am deeply grateful to them not only for being great mentors to me with their tremendous knowledge and vision on academic research, but also for being approachable and encouraging all the time.

I am grateful to Turkish Armed Forces and Turkish Military Academy for the opportunity to continue my education in graduate school here in the United States. Being in the Turkish Military provided another life-changing opportunity to me, which is having the chance to know all the greatest friends I have. I will always feel lucky for knowing them.

Most importantly, I want to thank my family back in Turkey, who has always been there for me. I can feel their unconditional love and support from thousand miles away. I would like to express my deepest gratitude to my beloved wife, Tugba, for her endless support, and to my lovely daughter Seyda, for instantly making life beautiful to me with her existence no matter whatever happens in my life.

This thesis is dedicated to the memory of Hubeyb Turan. I will always be proud to have known you.

TABLE OF CONTENTS

	Page
ACKNOWLEDGEMENTS	iii
LIST OF TABLES	vi
LIST OF FIGURES	vii
CHAPTER 1 INTRODUCTION	1
CHAPTER 2 LITERATURE REVIEW	4
2.1 Social Group Categorization and Western/Non-Western Divide	4
2.2 Using Topic Sentiment Analysis for Dramatic Events	10
CHAPTER 3 PROFILES OF FOUR CASES AND COUNTRIES	13
CHAPTER 4 METHODS	17
4.1 Data Collection, Sampling and Cleaning	17
4.2 Measurement	19
4.2.1 Dependent Variables	19
4.2.2 Independent and Control Variables	20
4.3 Analysis	21
4.3.1 Sentiment Analysis	21
4.3.2 Topic Modeling	21
4.3.3 Correspondence Analysis (Topic Sentiment Analysis)	22
4.3.4 Regression Analyses	23
CHAPTER 5 RESULTS	24
5.1 Descriptive Statistics	24
5.2 Correspondence Analysis (Topic Sentiment Analysis) Results	24
5.3 Ordinal Logistic Regression Results for Popularity Score	25
5.4 OLS Regression Analysis Results for Sentiment Score	26
CHAPTER 6 DISCUSSION OF TOPICS	29
6.1 Topic 1. Muslims, Refugees and Terrorism	29
6.2 Topic 2. Reporting the News	29
6.3 Topic 3. Anger and Cursing	29

6.4	Topic 4. Sympathy for Paris	30
6.5	Topic 5. Religion and Making Generalizations	30
6.6	Common Themes in All of the Topics.....	31
CHAPTER 7 CONCLUSION.....		33
REFERENCES		47

LIST OF TABLES

	Page
1. A Sample of Headlines from Newspapers about the Differences in Reactions to Terrorist Attacks	39
2. Comparison of Four Terrorist Attacks of Interest.....	39
3. Comparison of Four Countries of Interest	40
4. Distribution of Frequency for Commenters' Nationalities	41
5. Topics, Terms and Number of Comments for Each Topic.....	42
6. Descriptive Statistics of the Variables in the First Part of the Study.....	43
7. Descriptive Statistics of the Variables in the Second Part of the Study	44
8. Ordinal Logistic Regression Analysis Estimates Predicting Popularity Score.....	45
9. OLS Regression Analysis Estimates Predicting Sentiment Scores	46

LIST OF FIGURES

	Page
1. Total Number of Terrorism Incidents between 1968-2009	36
2. State Fragility Index of France, Turkey, Belgium, and Paris (1995-2014)	37
3. Topic Sentiment Map.....	38

CHAPTER 1

INTRODUCTION

Humanity suffers from terrorist attacks in recent decades more than ever it did throughout the history (see Figure 1). The possibility of a terrorist attack to occur in any country and being a threat to lives of civilian citizens is more than any other kind of conflicts. This made terrorism relevant for every human being, which makes it a social and political phenomenon with serious consequences. One of the many aspects that have been debated widely in platforms such as mass and social media is the discrepancy in people's reactions to terror attacks depending on whether it happened in a Western country or not.

Do terrorist attacks that occur in a Western country draw more attention than terrorist attacks that occur in the rest of the world? Considering the symptoms such as leaders of the countries assembling in Paris after Charlie Hebdo attack, or Facebook raising some eyebrows for providing safety check and flag features for some countries and not for others (Hennessy 2016, Mandhai 2015), or hashtags that have gone viral after some attacks (Cookman 2016), it seems that some terrorist attacks resonated more than others at first glance (see Table 1). If this is the case, what dynamics can explain this difference? Columnists and social media users speculated on some potential reasons such as familiarity, number of victims, and the difference in expectations of a country to be a stage for a terrorist attack. An academic perspective, more specifically a sociological one, is needed to bring light to this debate.

To explain the reasons of discrepancy in reactions and to understand the nature of the discourse after terrorist attacks, it is necessary to understand the process of social identification. This paper uses social psychological theories on social identity formation to explain how people construct social identities and how these socially constructed identities shape people's reactions to terrorist attacks. The discussion is supported with insights from two historically based theses

on Western/Non-Western relations: Edward Said's *Orientalism* and Huntington's *The Clash of Civilizations*.

Social media comments are analyzed in the current study, using topic modeling and sentiment analysis, which are text mining methods that uncovers what topics are predominantly discussed in a text corpus. By this way, the discourse after terrorist attacks, and if there is a discrepancy of reactions towards terrorist attacks based on the civilization it belongs, could be revealed.

The data for this study are Reddit comments. Reddit is specifically chosen as the data source for this study for three reasons. First, it is a platform for people to comment, which is focused on the open discussion about the topic of interest. Second, Reddit is neater and the discussion remains more relevant compared to other social media platforms such as Twitter or YouTube because the discussion is not distracted by elements of videos or people trying to have more followers. Third, Reddit users comment through aliases. Social media posts in the platforms allowing aliases for users are convenient to observe public opinion on controversial issues. In this kind of platforms, social desirability is less of a concern because people feel anonymous. They write their opinions more comfortably when they do not feel a social pressure.

The study consists of two parts. In the first part, I aimed to explore what determines the public interest and support and to find out if it differentiates between cases. For this reason, the popularity scores (or vote) that each comment received from readers of Reddit are scraped, which is the dependent variable of the first part of this study. Three Ordinal Logistic Regression models are fitted. In the first model, the dependent variable is regressed on the independent variables, happening in a Western/Non-Western country and sentiment score of comments. In the second model, a control variable is included, which is casualty. Finally, topic variables that are obtained from topic modeling are included in the third model.

In the second part, the nature of the discourse on terrorism and what topics are discussed after different terror events is explored. To fulfill this purpose, sentiment analysis is conducted as a first step to obtain emotional valence of each comment. Following that step, a topic model is produced to uncover the latent topics that are discussed after the events occurred. Thirdly, topic sentiment analysis, the correspondence analysis of topics and sentiments, is conducted to show which topics correspond to which sentiments and cases. Then, an OLS regression model is executed to predict sentiment scores with topic variables. Finally, the reasons why these topics appeared in the first place and why they are related with specific sentiments are discussed.

CHAPTER 2

LITERATURE REVIEW

2.1 Social Group Categorization and Western/Non-Western Divide

Dichotomous classification of Western and Non-Western is actually about how people identify themselves and their social groups. In social psychology, this phenomenon is explained with social identity theory (Tajfel and Turner 1979; Turner 1982; Rabbie, Schot and Visser 1989; Hogg, Terry and White 1995). According to this theory, people tend to identify themselves as “us” vs. “them”. Based on this two-fold categorization, our perceptions of our group and other groups are shaped.

Every person has several social identities, because people are part of many different social groups (Oswald 2005). However, people emphasize some social identities over others based on the social context. Some scholars put forward nationality as a common basis for self-categorization (Ellemers, Spears, and Doosje, 2002; Turner, Oakes, Haslam, and McGarty, 1994). In his study about post-9/11 reactions, Oswald (2005) cited George Bush’s statement, “Either you are with us, or you are with the terrorists”, as an example of social categorization in the context of terrorism. It may be hard to distinguish if “us” refers to a nationality or to a higher-level concept, civilization. She interpreted this categorization after 9/11 as the rise of self-categorization based on American national identity because the other was defined as Arab, according to her. Whether this interpretation was true in the case of 9/11 is not going to be discussed here. However, the identification of in-group has evolved to West because the identification of out-group, or the other, went beyond Arab (Pratt 2016). This paper argues that the social identification is embodied as Western and Non-Western, in the context of terrorism.

“West vs. the Rest” is a concept that became popular with the influential article of Samuel Huntington, “The Clash of Civilizations?”. Huntington (1993) pigeonholed civilizations

under 8 categories: Western, Slavic-Orthodox, Latin American, Islamic, African, Confucian, Japanese and Hindu. He argued that fundamental differences among civilizations are becoming more crystalized and civilization-based self-identification increases with the spread of global values because this process is generally considered as dictation of Western values over Non-Western cultures. According to Huntington (1993), these fundamental civilizational differences will be the main basis of conflict in the future.

Western/Non-Western type of dichotomous categorization is rooted in the history. It goes back to the experiences from colonialism and scientific revolution. There are two highly relevant concepts that need to be included to the discussion here: othering and Orientalism. Although othering is a concept firstly used by Spivak (1985), according to Jensen (2011), the necessity of *other* to signify *self* is an idea going back to Hegel. It has an exclusive basis working through externalizing some unwanted features that are not ascribed to the in-group, to the out-group (Barnett 2006). Jensen (2011) expressed othering as ‘symbolic degradation’ and understood the concept as a way to construct identity through this degradation. The members of the in-group portrays the other by ascribing negative characteristics, at least as they perceive it, to the out-group and caricaturizing them. For an instance, Said (1978) stated that Western people have always pictured Muslims and Arabs as barbaric and inclined to violence.

Another reason behind the “West vs. the Rest” kind of self-categorization is the power of the West. Western has been commonly seen as superior to the Rest (Sewpaul 2016). Huntington (1993) stated that the West is incomparably powerful than the other civilizations in terms of military capacity. Said (1978) stated that Western dominance on the Rest is beyond military and politics; it is also cultural. According to him (1978), the existence of Orientalist discourse is a means to solidify the socially constructed cultural hierarchy between two groups. Even if it is still true for every civilization after more than two decades is the topic of another discussion, but

it is safe to say that it is superior, in terms of military and economic power, to the out-group categorized as Islamic civilization. According to Oswald (2015), when people perceive their in-group as more powerful than out-group, they are more likely to support negative actions and they tend to express outrage and hatred toward the out-group.

The concept of other reached to the peak of its popularity with Edward Said's seminal book, *Orientalism*. Said (1978) argued that the Western identity is merely formed based on its other, the East. Orientalism is the name of this self-identification process for the West by defining the East as 'the other' and distancing itself from that. As it can be understood from the previous statement, Said saw the relationship between West and the Orient as a socially constructed reality. This binary self-identification as Westerners and Non-Westerners came into being in the postcolonial era (Chakrabarti 2012). When the relationship between the West and the East is addressed through this dichotomy, members of both categories ends up in a position that is more distinct to each other (Said 1978).

Another social psychological perspective on intergroup relationships is the existence of the feeling of being threatened. There are two theories on this matter: realistic conflict theory (Bobo 1988; Quillian 1995; Sherif 1966) and integrated threat theory (Stephan, Diaz-Loving, and Duran 2000; Stephan and Stephan 2000). According to realistic conflict theory, in-group coherence and out-group animosity increases if in-group is intimidated by an out-group. Integrated threat theory incorporated symbolic threats such as lifestyle, culture and beliefs to the realistic threats proposed by realistic conflict theory. Socially constructed differences between in-group and out-group are perceived as a hazard for the integrity of the in-group by its members (Mammone, Godin, & Jenkins, 2012). In order to make in-group safe from this hazard, the out-group is reflected as inferior to the in-group. Oswald (2005) argued that perceiving threat might promote out-group deprecation (see also Brewer 2001).

The distinction between Western and Non-Western is beyond geography. It is about values. Some studies tried to explain the progress of the West with values like competitiveness and work ethic, of which West possesses and the Rest lacks (Ferguson 2012). Sewpaul (2016) stated that the West and the Rest are dichotomized by associating the former with liberalism, individualism, egalitarianism and pragmatism, while the latter with authoritarianism, patriarchal social structure, and collectivism. Considering the integrated threat theory, these differences in values have the potential to be perceived as symbolic threats and the characteristics of the other group may be reflected as inferior.

Every group needs an 'other' (or others) to solidify its group identity and cohesion. Islamic civilization stood out as the other, among other civilizations of the Rest. According to (Pratt 2016), Islam is imaged as the *de facto* ideological opponent of the West. Muslims are identified by Western perspective as 'them', which intimidates the West, which is 'us' according to their perspective (Kassaye, Ashur and Van Heelsum 2016; Osuri and Banerjee 2004). The out-group identification may be mainly based on Islam for three reasons. First, "the Rest" is too broad and intangible, defining out-group as Islam solidified "the Rest." Second, there is an obvious physical threat coming from several terrorist groups, such as ISIS or Al-Qaida, that claim they are acting in the name of Islam, which leads to a generalization that is popularly referred as Islamophobia. Third, Islamic lifestyle is perceived as a more urgent and irreconcilable symbolic threat than other groups defined under "the Rest." Numerous scholars also confirmed that Muslim minorities and Islamic world as a whole are described as a significant threat to Western lifestyle (Kassaye et al. 2016; Richardson 2004; Saeed 2007). Pratt (2016:35) stated that Islam is perceived in the context of Huntington's clash of civilizations as "the historical antithesis to the West's thesis" or as the "Great Threat" to Judeo-Christian West, in Huntington's

(1993) words. Nourbakhsh (2013:111) named the tension between the West and the Muslim world as a second Cold War.

The aversion between Western in-group and Muslim other is widened because Western mass media has promoted the controlling images of Muslims as terrorists and depicted Middle East with lack of civilization (Hirchi 2007). Western media and film industry are commonly criticized with othering Arabs and Muslims and reflecting them as terrorists (see Saeed 2007, Shaheen 2003). Said (1980) argued that Islam is addressed and reported by the West in a different manner, compared to other Non-Western groups. Ahmed and Matthes (2016) found that media pictures Muslims in a negative manner and Islam as violent. In Western media, Anti-Muslim rhetoric has found a place to itself since Iranian revolution of 1979, according to Said (1997). For Westerners, Muslims are “an undifferentiated mob of scimitar-waving oil-suppliers” and Islam is unreasonably oppressive against women, as Said (1980:19) asserted. Jackson (2010) argued that the perception the US media creates, makes Muslims’ sufferings ‘acceptable’ for Americans. In sum, Western mass media has been influential in the process of caricaturizing Muslims as the irreconcilable other.

The public opinion on Muslims has been shaped mainly by media coverage until recently because the interaction of Westerners with Muslims was limited before social media. Naturally, there are numerous studies on how the perception of Islam is shaped by media (see Ahmet and Matthes 2016, Jackson 2010, Said 1997, Saeed 2007, Richardson 2004). However, the studies on the impact of social media are relatively limited. This study inquires how social media functions on this matter.

The tension between Westerners and Muslims exacerbates after terrorist attacks in Western countries by terrorist organizations like ISIS. Use of controlling images to depict Muslims has become more common in America after 9/11 attacks (see Oswald 2005). Jackson

(2010) claimed that constant coverage of controlling images of Muslims by mass media fortifies people's tendency to associate being Muslim with terrorism. According to social constructionist school of thought, terrorism is not a genuine problem that is brought about merely by the actions of a group of people (McQueeney 2014). However, it is formed within society based on what attackers claim, how they use symbolic means to catch public attention and manipulate prevailing opinion and sentiment, and how the meaning of attacks are perceived by society (Schmid and Jongman 1988; Turk 2004). Therefore, public response to terrorist attacks can provide us insights about how people identify their in-group and out-group.

In a similar study about social media responses to terrorism, Burnap et al. (2014) studied a terrorist attack in London in 2013. Using Twitter data, they developed statistical models to estimate the extent (retweet count) and permanence (time period between first and last retweet) of the information flow about the event. They stated that the amount of retweets indicate "the level of public interest and endorsement of the information (Burnap et al. 2014:206)". Upvoting and downvoting comments in Reddit has similar functions to retweeting. People upvote the comments they agree with, and vice versa. Furthermore, it also means endorsing comments because upvoted comments become more visible in a thread. I argue that the level of public interest to a terrorist incident happened in a Western country is going to be higher than an incident in a Non-Western country. Therefore, the comments on terrorist incidents in Western countries are going to be read and voted more than the incidents in other parts of the world. Based on this argument, the first hypothesis is stated as follows:

H1: Comments on Western cases are more likely to get higher popularity scores than comments on Non-Western cases.

Estimating sentiment values is another way to analyze public responses to terrorism. It is also meaningful to follow how the collective emotions about an event evolve through time

(Gaspar et al. 2015). In the studies about the relationship between sentiments and public opinion, there is a disagreement on whether sentiment of an expression effects how much it is endorsed. Tsur and Rappoport (2012) ascertained that sentimental nature of hashtags is not relevant to the endorsement of content. On the contrary, Berger and Milkman (2012) uncovered that audiences are more likely to share content with positive sentiment rather than negative. Burnap et al. (2014) found that sentiment of a Tweet significantly predicts the extent and permanence of information flows. According to their results, content that are expressed with positive sentiments are more likely to be endorsed and last longer compared to negative content. In my opinion, the endorsement of positive or negative content depends on the context. Therefore, I argue that the comments with a negative sentiment are going to draw more public attention than positive comments. The second hypothesis is as follows:

H2: Comments with a more negative sentiment are more likely to receive higher popularity scores from readers.

2.2 Using Topic Sentiment Analysis for Dramatic Events

Sentiment analysis has been used to bring out the emotions of people on the things they talk or write about. It is a text mining method, which is conducted through a word list consisting of words indicating positive and negative sentiments. It is also known as opinion mining. It ascertains units of text as positive, negative or neutral based on the frequencies of positive and negative sentiment terms. However, Gaspar et al. (2015) criticized quantitative sentiment analysis with downsizing emotions to positive and negative. They argued that negative is not inherently bad, just like positive not being inherently good. In other words, positive or negative valences of text units do not say enough about their content. Instead, they conducted a qualitative sentiment analysis to discover how people's reactions to unexpected stressful events function in

several ways. According to them, including a human-based element would increase the general understanding about the topic of interest. In addition to their critique of quantitative sentiment analysis, they acknowledge the validity limitations of qualitative sentiment analysis. They offered mixed methods using both computer-based and human-based methods to overcome all the limitations. To achieve this purpose, a topic model is generated in this paper, in addition to sentiment analysis.

Topic modeling is a computer-based text mining method that uses a specific algorithm to discover predominant topics and terms in a text corpus. It is a technique that becomes increasingly popular in social scientific research. It uncovers latent topics in the text and lists prominent terms for each topic. Then researcher can define the topics qualitatively. Ignatow, Evangelopoulos and Zougris (2016:263) defined topic models as “statistical models and techniques for automatically identifying latent topics in large document collections”. According to Ignatow et al. (2016), topic modeling has three basic assumptions: the existence of latent topics, word-document co-occurrences as indicators of topics and the existence of the relationship between words, topics and documents (see also Cai et al. 2008). It can be used to analyze huge amount of text corpora, which make it an useful complementary tool, and even an alternative in some cases, to other widely used methods to analyze textual data such as content analysis, especially in the steps of reading and coding (Chuang et al. 2014, Papadouka, Evangelopoulos and Ignatow 2016).

Cheong and Lee (2010) adopted a different approach towards this matter. They formed seven new categories for reactions to terrorism cases and feeded sentiment lexicon with potential keywords, referring to Beutler et al. (2006) and Clark (2009). These categories are “Emotion:fear/anxiety”, “Emotion:shock”, “Response”, “Need for information and updates”, “Assessment:threats”, “Assessment:casualties”, and “Response and law enforcement” (Cheong

and Lee 2010:51). Even though they formed these categories for sentiment analysis, what they meant to do was topic modeling because categories other than first and second categories are not event sentiments.

Different than what Gaspar et al. (2015) and Cheong and Lee (2010) did, I argue that topic modeling is the way to include human-element. On the one side, this way of analyzing social media comments is more feasible because data may consist of thousands of units (comments, Tweets etc.) when using unstructured data, which makes reading word by word very difficult, if not impossible. On the other side, it would be a waste of data to choose a small sample to read and interpret qualitatively. Blending sentiment analysis with topic modeling is a more convenient way to grasp the nature of the reactions to terrorist events than enforcing top-down categories because terrorism and discourse on terrorism changes. Mei et al. (2007) argued that the increases in positive and negative emotions can be observed in topic-sentiment mixtures (TSM) when there are relevant events to topics, which are terrorist attacks in this case. In sum, topics that are obtained through topic modeling can explain the differences in people's emotional reactions to terrorism. I argue that topics of comments are relevant and significantly predict the sentiment tones of comments. Therefore, the third hypothesis is as follows:

H3: The topic of a comment significantly predicts its sentimental valence.

CHAPTER 3

PROFILES OF FOUR CASES AND COUNTRIES

In this section, some background information is provided about terrorist cases and the countries the occurred in. Four cases of terrorist attacks are selected for the purposes of this study: November 2015 Paris attack, October 2015 Ankara attack, March 2016 Brussels attack and March 2016 Lahore attack.

These four cases are chosen considering John Stuart Mill's *method of difference*. Millian *method of difference* basically aims to minimize all factors other than the factor that is interested to infer that the differences in the outcome are caused by the factor that is isolated (Mill 1884). It is similar to turning everyday events into an experiment as much as possible. This method is highly convenient for such a social phenomenon as much as the cases I selected are convenient for method of difference.

Most of the factors that could be considered as potential determinants for differences in people's reactions to terrorist events are naturally eliminated in the four cases I selected. First, none of the cities that these four attacks occurred are war zones. It means that a huge number of people dying in those cities is not everyday news. Second, all of the cities are one of the two biggest cities of their countries and all of them except Lahore are capital cities. It may mean that they are potential targets for terrorism intrinsically but they are also well-protected against terrorism threat in the countries they belong. Third, all of the attacks happened in 2015 and 2016. A 2-years-period is a fairly close-range. It is safe to assume that there are not any periodical differences. Fourth, all of the four countries that suffered from these attacks are non-English-speaking countries. It prevents a potential bias in the data and analysis since only English comments are included in this study. Fifth, the groups are all "so-called" Islamic groups. All

these similarities helped to isolate the variable “being in a Western or Non-Western country” as much as possible.

Beside these similarities, there are many differences between four cases and countries that should be mentioned. After providing the general information about terrorist attacks, a set of information about the countries is provided for different purposes. First, the number of Internet users in each country is included (Internet Live Stats 2016). The reason to include this is the potential bias that limited access to Internet may cause. For this kind of a purpose, the relevant statistics is the number of users, not the percentage. However, we see that the a Reddit thread about the Belgium attack is the second most commented thread among the four cases, even though Belgium has the lowest number of Internet users.

Secondly, two indexes are provided: Global Terrorism Index (GTI) and Fragile States Index (see Global Terrorism Index 2015; Fragile States Index 2016). These indexes are included for the same reason: to have an idea about people’s preconceptions on France, Belgium, Turkey and Pakistan. People may tend to react dramatic events differently based on how they perceive the countries the events happened. Global Terrorism Index is a report on terrorism, which is published by Institute for Economics and Peace annually. The second index, Fragile States Index, has a broader scope. It is published by a non-profit research organization, The Fund for Peace, annually. It is estimated through a diverse set of numerous social, economic, political and military variables ranging from natural disasters, refugees per capita, ethnic/religious violence, and human capital to corruption, criminality, press freedom and GDP per capita. The indicators are pigeonholed under 12 main categories: demographic pressures, refuges and IDPs, group grievance, the higher values indicate more fragile states.

The attack in Paris, France happened on November 13, 2015. ISIS, the second deadliest terrorist organization in the world after Boko Haram (Global Terrorism Index 2015), claimed responsibility for the attack. 130 people were killed and 368 were injured.

The bombings in Ankara took place on October 10, 2015. It is the deadliest terrorist attack in the history of Turkey. The perpetrators were linked to ISIS, even though they did not claim responsibility. 103 people were killed and 508 were injured.

The bombings in Brussels happened on March 22, 2016. ISIS claimed responsibility for the bombings. There were 32 victims and 340 injured. It is the deadliest terrorist attack that Belgium ever faced.

The bombing in Lahore took place on March 2016, which was Easter Sunday. There were 75 victims and 340 injured. Jamaat-ul Ahrar claimed the responsibility for the attack, which is a terrorist group affiliated with Pakistani Taliban.

France is a Western country in terms of Huntington's civilizations. There are 55,860,330 Internet users (86.4% of the population) in France. GTI score of France is 4.553 out of 10. It is the 36th country that is most affected from terrorism in the world. State fragility index value is 34.5 for France (158th most fragile country out of 178 countries).

Turkey belongs to Islamic civilization, according to Huntington's description of civilizations. There are 46,196,720 Internet users (58% of the population) in Turkey. GTI score of Turkey is 5.737 out of 10. It is the 27th country that is most affected from terrorism in the world. State fragility index value is 77.3 for Turkey (79th in the world).

Belgium is also in Western civilization like France. There are 10,060,745 Internet users (88.5% of the population) in Belgium. GTI score of Belgium is 1.977 out of 10. It is the 82th

country that is most affected from terrorism in the world. State fragility index value is 29 for Belgium (164th in the world).

Pakistan is a country that can be categorized under Islamic civilization. There are 34,342,400 Internet users (17.8% of the population) in Pakistan. GTI score of Pakistan is 9.065 out of 10. It is the 4th country that is most affected from terrorism in the world. State fragility index value is 101.7 for Pakistan (14th most fragile country in the world).

CHAPTER 4

METHODS

4.1 Data Collection, Sampling and Cleaning

Analyzing data from social media platforms is especially important when an undesirable event, such as terrorist attacks, diseases or food contamination incidents, come about (Gaspar et al. 2015). People can freely express their emotions and ideas on these platforms without any concern of social desirability. This is a fruitful source of data to understand public opinion and reactions to dramatic events than conventionally collected data, such as surveys or interviews, when the purpose is. For this reason, a social media platform, Reddit, is chosen as the data source to analyze this phenomenon.

Reddit comments and popularity scores (votes) for each comment are scraped using R packages, *rvest* and *RSelenium*. *Rvest* scrapes data from web pages using CSS catchers of the elements (comments and popularity scores) in the page. *RSelenium* is for commanding a web browser through an Integrated Development Environment (IDE) for R, which is RStudio in our case. *RSelenium* is needed because Reddit only allows for readers to reach top 500 comments through web link and it was necessary to click “show more comments” button manually to see more comments.

Relevance sampling, a non-probabilistic sampling technique, is used in this study to select the four terrorism incidents. Sampling methods is generally not stated specifically in this kind of studies because it comes by itself for text analysis data sampling (Ignatow et al. 2016, Krippendorff 2012). Comments from Reddit threads about each terrorist attack are scraped using R. The threads are selected from “worldnews” subreddit, which is one of the most popular subreddits of Reddit where the international events are posted and discussed.

After selecting the cases and downloading the comments, the data are cleaned from non-English comments. 10% of the comments are randomly sampled, which means 2833 comments for Paris attack, 185 comments for Ankara attack, 2083 comments for Brussels attack, and 523 comments for Lahore attack. Sampling is conducted based on percentage instead of a fixed number (e.g. 1000 comments from each case) because it would cause a bias in the sample since the total numbers of comments for each case are substantially different from each other.

After cleaning the data, comments are sorted in a descending order based on the popularity score they received from readers, since these scores reflect the public opinion about a comment, which is the main focus of this study. Even though LSA does not require for different collection of documents to be in an equal amount to process them, I included an equal amount of comments for each case to the analysis because truncating the collection with more text to equalize it to the other collection is advised in order to make the cases to be compared as resembling as possible (Ignatow et al. 2016). For this reason, data of this study consists of 1450 Reddit comments for each of the four terrorist attacks, which makes 5800 comments in total.

To be familiar with the population of commenters that is analyzed, 50 comments from each case are randomly sampled. Using the user id of the commenters, user pages of commenters on Reddit are found. A user page only contains the comments that are written by a user. I identified users' country of origin and whether they are native English speakers or not by qualitatively analyzing their comments. Looking for comments written in another language or expressions, which may help to identify the user, such as *our country*, *As a Brit, I'll vote for...*, I profiled a sample of users that commented on the issues I research. Even though most of the comments can easily be profiled with a brief overview, I excluded the users, whose country of origin and language cannot be deducted with a statement that obviously reveals that kind of a deduction. In addition, there are also comments in this study, which do not have username

information because Reddit moderators may delete usernames of the commenters of specific comments for different reasons. These comments are excluded as well. All of these excluded comments are replaced with new random comments.

According to this sample, 112 out of 200 commenters, who commented on the attacks, are American (%64). There are 19 Turkish (%9.5), 16 British (%8), 10 Canadian (%5), and 6 French commenters (%3) in total. The remaining 37 commenters (%18.5) are from the following countries: Germany, Australia, Pakistan, Belgium, Pakistan, India, Singapore, Indonesia, Armenia, Norway, Spain, Portugal, Denmark, Bosnia, Switzerland, Sweden, Serbia, Iran, Finland, Netherlands and Croatian. 3 of the commenters could only be identified as European, but not identified in a specific country. 144 of the commenters (%72) are native English speakers, while 56 of them (%28) are non-native English speakers. The frequencies and percentages of the commenters for each case are presented in table 4.

4.2 Measurement

4.2.1 Dependent Variables

Popularity score: The first dependent variable of the study is popularity score. The variable consists of the sum of upvotes and downvotes a comment receive from readers. The scores range from -114 (most downvoted) to 5592 (most upvoted). The absolute values are taken because it is argued in this paper that the comments on Western cases are going to receive more votes, no matter what the direction is. Since the values are positively skewed, it does not meet the normality assumption of OLS regression. Therefore, the popularity scores are collapsed into three categories as not voted at all (0), lowly voted (1), and highly voted (2)

Sentiment score: Second dependent variable of the study is sentiment scores of comments, which are produced with the sentiment analysis. The variable is normally distributed, ranging from -20 to 7, going from the most negative sentimental tone (-20) in a comment towards the most positive (7).

4.2.2 Independent and Control Variables

Western: Western is the independent variable for the second part of the study. It is a dichotomous variable, consisting of Western and Non-Western categories. The comments on Paris and Brussels attacks are coded as Western (1), while the comments on Ankara and Lahore attacks are coded as Non-Western (2). It is dummy coded for the analysis. Non-Western is chosen as the reference category.

Sentiment Score: Sentiment scores obtained from the sentiment analysis is an independent variable in the first part of the study. It is the same variable that is explained in the dependent variables.

Casualty: The number of victims is a control variable for the first part of the study. It is an interval-ratio variable, indicating the number of victims for each case (Ankara=109, Paris=137, Brussels=35, Lahore=72).

Topics: Five most prominent topics in the text corpus are produced with topic modeling. A variable is produced for each topic. Based on their topic terms, the topics are labeled as follows: Muslims, Refugees and Terrorism (T1), Reporting the News (T2), Anger and Cursing (T3), Sympathy for Paris (T4), and Religion and Making Generalizations (T5). The topic model, which is produced in SAS Enterprise Miner, provided factor loadings of the topics for each comment. The factor loadings range from -0.19 to 0.66. Higher values of factor loadings in a

specific topic indicate that a comment contains more components that are relevant to that topic. In other words, the higher factor loading of a topic a comment has, the more it is about that topic.

Interaction Variable of Western and Casualty: An interaction variable is created to see if the relationship between the casualty of event and the popularity score a comment receive differs between the categories of Western and Non-Western.

4.3 Analysis

4.3.1 Sentiment Analysis

Sentiment analysis is conducted using R, a statistical programming language. The lexicon for positive and negative words, generated by Hu and Liu (2004), is used. Using the frequency of these positive and negative words, sentiment analysis assigns a value to each comment demonstrating how negative or positive they are. I included the outcome of sentiment analysis as an independent variable to the first part and as the dependent variable to the second part. The descriptive statistics of the sentiment score variable will be provided later in the measurement section.

4.3.2 Topic Modeling

Topic modeling is a text mining method can be conducted using several techniques. Two main algorithms that are used in topic modeling are Latent Dirichlet Allocation (LDA) and Latent Semantic Analysis (LSA). LDA extracts topics based on a probabilistic approach, while LSA uses patterns and similarities of words, in terms of meaning, to detect topics. LSA can be implemented faster than LDA. In addition, it always gives the same results for same data, while the results in LDA vary slightly in every implementation. LDA is preferred by majority of the researchers because it is regarded as a better model in terms of its statistical basis (Ignatow et al.

2016) but LSA gives better results in cognitive processes, besides its other advantages such as being faster, simpler and more consistent, according to Evangelopoulos (2013). Ignatow et al. (2016) adjusted “Topic Sentiment Analysis” for social scientific studies by using LSA instead of LDA. These characteristics of LSA may make it a better choice for this study. Text mining module of SAS Enterprise Miner, which applies Latent Semantic Analysis, is used to generate the topic model. After conducting Singular Value Decomposition (SVD), 5 topics with the highest eigenvalues are selected.

As a result of topic extraction, we obtained 8 topics. 4 of the topics are mainly about specific cases (T2 is about Brussels attack, T3 is about Ankara attack, T5 is about Paris attack, and T7 is about Lahore attack). These topics provide insights about how reactions to each case are evolved. The rest of the topics demonstrate the general discussion people’s reactions to terrorism in general.

4.3.3 Correspondence Analysis (Topic Sentiment Analysis)

After obtaining the topics, I conducted a correspondence analysis that demonstrates which topics correspond with which sentiments. Topic sentiment analysis is a newly developed text analysis method finding salient topics and corresponding sentiments in a text corpora (Ignatow et al. 2016; Lin and He 2009; Mei et al. 2007). It can be considered as an integration of topic modeling and sentiment analysis. There has been a need to integrate topic modeling and sentiment analysis because the conclusions are much more meaningful when the feeling people have towards the topics they discuss is known. This is the reason why topic sentiment analysis is developed. Mei et al. (2007) came up with *topic-sentiment mixtures* (TSM) and Lin and He (2009) developed *joint sentiment topic* (JST) to serve the aforementioned purpose.

Correspondence analysis uses principal components (dimensions) as x and y axes of the graph. The distances between rows and columns are meaningful and provide the proximity topics with other topics and sentiments. Since categorical variables can be observed better correspondence analysis, sentiment score variable is recoded as positive, negative and neutral. To visualize what comments with negative or positive sentiments are about, a symmetric correspondence analysis biplot for topics and sentiments is produced.

4.3.4 Regression Analyses

Ordinal Logistic Regression is conducted to explain the variation in the popularity score in the first part of the study. As it is explained in the measurements section, the popularity score variable (DV) is collapsed into three hierarchically ordered categories, which makes it convenient for ordinal logistic regression analysis. The assumption of parallel lines is verified with the test of parallel lines and no violation is detected.

In the second part of the study, ordinary least squares (OLS) regression is conducted to find out if topic of a comment can predict the change in sentiment values. Even though correspondence analysis is advantageous in terms of visual presentation, regression analysis is a better way to explain how topics are related to sentiments. Sentiment score variable (DV) is normally distributed, which means that it does not violate the normality assumption of OLS regression. Collinearity diagnostics are checked and no issues of multicollinearity are detected.

CHAPTER 5

RESULTS

5.1 Descriptive Statistics

The means, standard deviations, minimum and maximum variables are presented in the tables 6 and 7. The descriptive statistics results show that the mean score for the popularity score is .824 with a standard deviation of .64. This result indicates that the average popularity score is somewhere between not voted and lowly voted, on average. The mean score of Western variable is .87, which means that 87% of the comments are posted to Western cases. The average sentiment score is -.451 with a standard deviation of 1.58. The mean score for casualty is 87.70 with a standard deviation of 38.43. It indicates that the average number of victims for four cases is 88. The descriptive statistics results for factor loadings of topics are presented in Table 7.

5.2 Correspondence Analysis (Topic Sentiment Analysis) Results

In the topic sentiment biplot, it can be seen that topic 4 (Sympathy for Paris) is close to positive and very positive sentiment nodes. Topic 2 (Reporting the news) and is close to the neutral sentiment node. Topics 1 (Muslims, Refugees and Terrorism), 3 (Anger and Cursing) and 5 (Religion and Making Generalizations) are gathered around negative and very negative sentiment nodes. All of topics appeared closer to the sentiments as it would be expected. The result can be interpreted in two ways. We can see what positive, negative and neutral reactions are about. Positive emotional reactions in our corpus mostly addressed the victims and their families in Paris attack. The negative reactions are mainly about religion, Muslims, refugees and

terrorism. It can also be interpreted the other way around. People address issues about Muslims, religion, and refugees with a negative language use. However, they express their feelings towards victims positively. People also seems to use a neutral language when providing information and reporting events.

5.3 Ordinal Logistic Regression Results for Popularity Score

Ordinal Logistic Regression results are presented in table 8. Four models are formed to execute multivariate analysis. In the first model, the independent variables, Western and sentiment scores, are included to the analysis. Casualty, the control variable, is included to the analysis in the second model. In the third model, topic variables are incorporated to the analysis. Finally, the interaction variable of Western and casualty is included to the analysis in the fourth model. Considering that it has the lowest -2loglikelihood value (10665.8) and the highest model χ^2 value ($\chi^2= 101.09$), it seems that the third model fitted the data better than other models. Third model explains %9.4 of the likelihood of receiving more popularity scores (Pseudo $R^2=.94$). Therefore, the third model is going to be interpreted.

Being a comment that is written on a Western case significantly predicts the probability of receiving more popularity score ($B=-.029$, $p \leq 0.01$). Comments on Western cases are 24.6% more likely to receive higher popularity scores than comments on Non-Western cases (Odds ratio=1.246, $1.246-1=.246$). The first hypothesis is supported by the results.

Sentiment score of a comment has a negative significant relationship with the popularity score in model 1 and 2, as I hypothesized. However, it is no longer significant in third model after the topic variables are introduced.

The number of casualties in a terrorist attack has a significant negative effect on the probability of receiving more popularity score ($B=-.029$, $p \leq 0.01$). The comments that are written on terrorist attacks with more casualties are less likely to receive more popularity scores than comments on attacks with fewer casualties.

There is a positive, highly significant relationship between being about topic 1 and the probability of receiving more popularity score ($B=2.912$, $p \leq 0.01$). The more a comment is about topic 1, the more it is likely to receive a higher popularity score.

Being about Topic 2 (Reporting the News) has no significant effect on the probability of receiving more popularity score.

Being a comment expressing anger significantly predicts the likelihood of receiving a higher popularity score ($B=1.370$, $p \leq 0.01$). Comments that contain more components of topic 3 are more likely to receive higher popularity scores.

There is a positive significant relationship between being a comment expressing sympathy for the victims of Paris attack and the probability of getting higher popularity scores ($B=1.544$, $p \leq 0.001$). The more a comment is about topic 4, the more it is likely to receive a higher popularity score.

Being about topic 5 also significantly predicts the probability of getting higher popularity scores ($B=1.544$, $p \leq 0.001$). Comments that are written about religion and making generalizations are more likely to receive higher popularity scores.

5.4 OLS Regression Analysis Results for Sentiment Score

Topics that are obtained through topic modeling explains %15.81 of the variance in sentiment score. Our hypothesis is supported by the results. All of the topics have significant relationships with the sentiment score. Since the topics cannot be known before topic modeling,

there was only one hypothesis about the significant relationship between topics and sentiment scores. Even so, the results are going to be interpreted.

There is a negative, highly significant relationship between commenting about Muslims, refugees and terrorism and the sentiment score of comments ($B = -4.216$, $p \leq 0.001$). People who are commenting on Muslims, refugees and terrorism are more likely to use a more negative language. For each unit increase in the factor loading of topic 1, the sentiment score decreases by 4.216.

There is a negative significant relationship between commenting to report the news and the sentiment score of comments ($B = -4.790$, $p \leq 0.001$). People who report the news and provide information about events are more likely to use a language with a more negative tone. For each unit increase in the factor loading of topic 2, the sentiment score decreases by 4.790.

Topic 3 also has a negative, significant relationship with the sentiment scores ($B = -7.636$, $p \leq 0.001$). When people are expressing their anger, they are more likely to use a more negative language. The sentiment score decreases by 7.636, for each unit increase in the factor loading of topic 3. Even though this result seems quite obvious, topic 3 is still important because it gives an idea about the emotion that negative comments are about.

There is a positive, significant relationship between comments expressing good wishes for the victims in Paris attack and the sentiment score ($B = .863$, $p \leq 0.05$). The sentiment score increases by .863 point for every unit increase in the factor loading of topic 4. People use a more positive language when they express their support and sympathy towards the victims of an attack. It is an interesting finding because it tells us about the nature of positive topics. Furthermore, it is in line with the literature on how concern for others may be positive, even though the emotion of concern is commonly regarded as negative.

Topic 5 has a negative, significant relationship with the sentiment score ($B = -5.703$, $p \leq 0.01$). For every unit increase in the factor loading of topic 5, the sentiment score decreases by 5.703 points. People use a language with a more negative tone when they write about religions and making generalizations in the context of a terrorist attack.

CHAPTER 6

DISCUSSION OF TOPICS

6.1 Topic 1. Muslims, Refugees and Terrorism

People discussed Muslims, Refugees and Terrorism in this topic. This topic clearly reflects how much social identity, realistic conflict and integrated threat theories are relevant in this context. When the comments on this topic are qualitatively analyzed, it can be seen that commenters from Western countries (in-group) commonly associate Muslims (out-group) with terrorism (physical threat). The link connecting this association to Westerners is the refugee crisis. Since the in-group wants to keep the out-group away, they strongly protest against taking refugees into their countries. It is important to note that there are also people who disagree this mentality and stand against it.

6.2 Topic 2. Reporting the News

This topic is about reporting the news and providing information about the events. In events like natural disasters, responses in social media are mostly about providing information; while in situations like economic crisis, people tend to blame authorities (Gaspar et al. 2015). In a terrorist attacks, it would be expected to see people blaming terrorists even if not authorities but the reactions in this case were prominently information providing, which is more similar to those in natural disasters compared to other cases. A potential reason may be that the Reddit thread about the attack is opened so soon and the facts about the attack were not clear yet and updates kept coming.

6.3 Topic 3. Anger and Cursing

Third topic is mostly about people stating their rage or cursing against different things, such as terrorists, ISIS, humans, Muslims or the killings in general. This topic also promotes our argument on how topic modeling complements sentiment analysis. This topic demonstrates what the negative sentiments that are obtained with sentiment analysis are really about. The predominant negative emotional reaction to terrorist attacks is anger. Reactions to dramatic events are generally seen as “aggregation of sentiment that needs to be ‘neutralised’ (Gaspar et al. 2015:180)” A statements with a negative tone does not mean that it is bad and needs to be eliminated (Lerner and Keltner 2000). How this collective negative feeling is directed is highly important for authorities and policy makers. In sum, this topic reveals an aspect of the nature of the negative sentiments that are aroused by terrorist attacks.

6.4 Topic 4. Sympathy for Paris

This topic is mainly about people expressing their support to French people. Gaspar et al. (2015) argued that “concern for others” is a positive emotion, even though concern is considered negative in general. It helps victims to cope with the tragedy relatively easier with the support of others. It also fortifies the rapports between people (Neubaum et al. 2014, Rime 2007). Even though it is referred as “concern for others” in the literature, it may also be seen as “concern for some of ours” in this case because this reaction is mainly directed towards victims of Paris attack, while this kind of a topic did not appear for other cases. Topic 4 also explains what positive sentiments are about.

6.5 Topic 5. Religion and Making Generalizations

This is a very common topic of discussion in Reddit or other social platforms, which mostly comes up after terrorist attacks. Some people clearly state their hate against Islam and

argue Islam (and all religions in some cases) is the reason behind these killings, while others respond by stating that terrorists are only a very small percentage that misinterprets Islam and they do not represent Islam. This topic is another indicator of how people identify “others” and try to stigmatize the out-group as a whole. The psychological motive behind these generalizations can also be interpreted through social identity theory and integrated threat theory. If terrorists are considered as a physical threat that is committed by a very small percentage of the out-group, it would not be possible for in-group (Westerners) to exclude the out-group (Muslims) as a whole. However, turning this physical threat into a symbolic one gives in-group the chance to accuse the all members of the out-group.

Extremist rhetoric against Islam and Muslims is becoming mainstream in the West (Pratt 2016). In other words, people in the center become more radicalized. He also indicates that discriminative expressions, which are once marginal, are normalized and more tolerated than before. Kassaye et al. (2016) found out that the debate around Muslims is predominantly negative and it excludes ‘the other’ in a similar logic with racism and xenophobia. The only difference is that it functions based on a religion rather than a physical difference or country of origin. This topic shows how this negative rhetoric and stigmatization become more widespread as an aftermath of terrorist attacks

6.6 Common Themes in All of the Topics

Innocence of the victims is emphasized in general. Rubin and Peplau (1975) argued that most people have a belief that the world is fair and everyone end up where they deserve. Seeing innocent people are killed ferociously by terrorists leads people to experience a cognitive dissonance, which is the stress caused by conflict between what is believed and what is observed

(Festinger 1962). This theme shows how this cognitive dissonance surfaces in reactions to terrorist attacks.

Another common theme in the comments is closely related to the main focus of this study. Lots of comments protest the difference in reactions to terrorist attacks. Some revealed their assumptions/disappointments about where these things happen. I explain this phenomenon with how people perceive things as "normal", even if it is the farthestmost thing to normal, when those things happen frequently. According to the report of IHS Jane's Terrorism and Insurgency Center (2016), the number of deaths from terrorism in the rest of the world is 42 times higher than the Western countries in a time period from January 2015 to June 2016 (Washington Post 2016). Therefore, when a terror attack happens in the West, where terrorist attacks are relatively rare; it means "getting out of normal" for Westerners, which causes more stress and louder reactions. However, when it happens in Pakistan, people may perceive it as "normal", since they believe that "it always happens there".

CHAPTER 7

CONCLUSION

In this study, I found that people approach events differently based on whether it happened in West or in the rest of the world. People remain to form social identities around Western/Non-Western civilizations and othering is still a relevant phenomenon. The vicious cycle that is driven by terrorism, polarization and othering had and will cause serious social problems in society. Gould and Klor (2004) reported that terrorist attacks committed by so-called Islamic groups like ISIS or Al-Qaida backfires on the Muslim communities in the Western countries because it makes it more difficult for them to assimilate into host society. For an instance, there has been an enormous surge in the number of hate crimes against Muslims after 9/11 (Gould and Klor 2014). Several studies argued that this backfiring effect is one of the purposes of those attacks because terrorists want to manipulate society in a way to put moderate Muslims in a more radical position (Gould and Klor 2014; Rosendorff and Sandler 2010). Terrorists would prefer moderate Muslims to be radicalized like themselves for many reasons like being easier to recruit, or slowing (if not stopping) the assimilation of Muslims.

Many scholars have studied the reasons that bring about terrorism and the ways terrorist organizations maintain their existence. Smelser and Mitchell (2002) asserted that the real dynamic behind the terrorism is inequalities in the world but it is overshadowed by the controlling images reflecting the problem as Muslims who are violent by nature. As Gergen (2009) stated, social problems are actually outcomes of power relations between various groups. Belamghari (2016) also stated that the inequalities that became more visible with globalization triggered terrorist attacks against Western civilization. In this study, I found that terror polarizes society and triggers an othering process based on Western-non-Western categories.

These terrorist attacks play a triggering role to the othering reactions. These polarizing reactions increase after major terrorist attacks. The clash of civilizations thesis and orientalism regained popularity during Bush administration (Kumar 2010). Furthermore, Kassaye et al. (2016:17) argued that Said's orientalism 'reappeared' in the Western thinking today. As it can be seen in the reactions after 9/11 (see Osuri and Banerjee 2004; el-Aswad 2013; Kumar 2010), negative and stereotypical public reactions against Islam are articulated more after large-scale terrorist attacks (Ahmet and Matthes 2016). Besides being an outcome of terror, this polarization leads to more terror. It is a vicious cycle.

Bhat (2015) argued that the exclusion of Muslims may turn into an identity crisis for them and may increase the tension between Muslims and non-Muslims in future. Kassaye et al. (2016) indicated that othering of Muslims may influence the integration of Muslims to society negatively and also affect Muslim self-identification (see also Guney 2010). Eliminating the othering caused by terrorism should be given importance. Koomen and Van Heelsum (2013) mentioned that the image of Muslim and the debates around Muslims are produced and dominated by non-Muslims than Muslims.

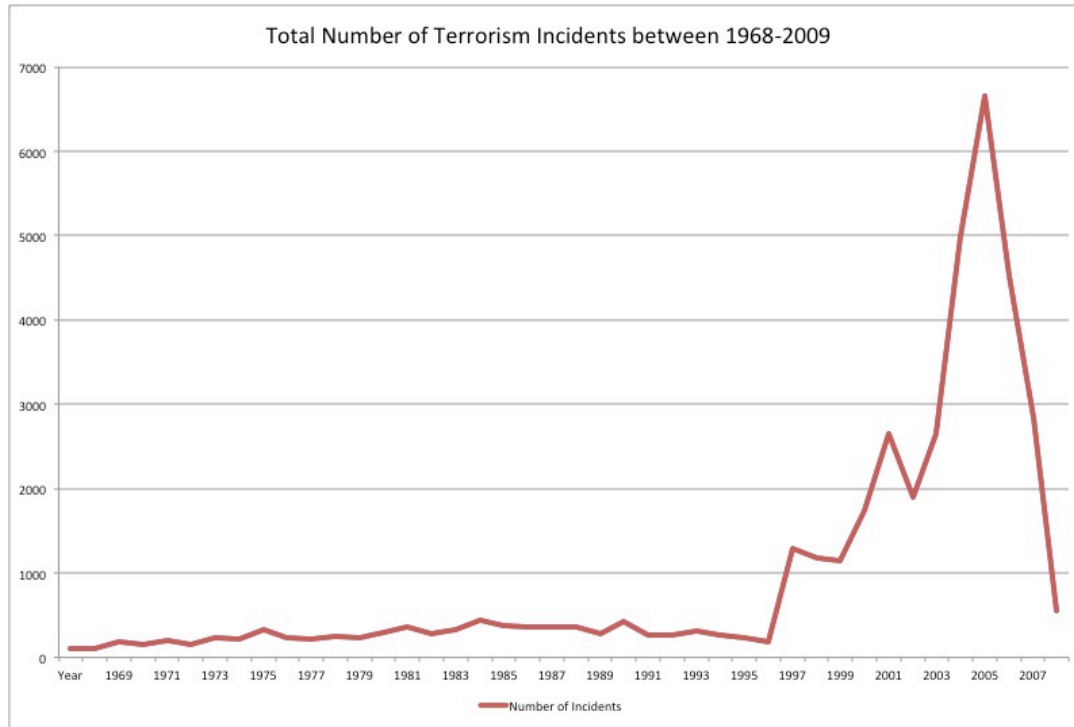
The study also shows that sentiment analysis can be utilized to organize the reactions of support (see Purohit et al. 2013). The method can also be helpful for authorities to profile the commenters, and also readers through popularity scores that comments receive, to have an idea of how they will react in a similar event in future (Lachian, Spence and Lin 2014). Mendes et al. (2001) argued that detecting especially the negative sentiment is important to figure out how people handle these unexpected situations.

This study is also an application of topic sentiment analysis. Gaspar et al. (2015) argued that sentiment analysis has three main limitations: one-dimensionality, being limited to a small set of emotions and not giving an idea about the purpose of expressions. Topic sentiment

analysis can be used to overcome these limitations. As Gaspar et al. (2015:186) stated, “Human-based qualitative sentiment analysis can be complex, time-consuming as well as not as scalable or easily comprehensible as a quantitative report of sentiment.” For this reason, a mixed method like topic sentiment analysis come to fore as a more feasible alternative.

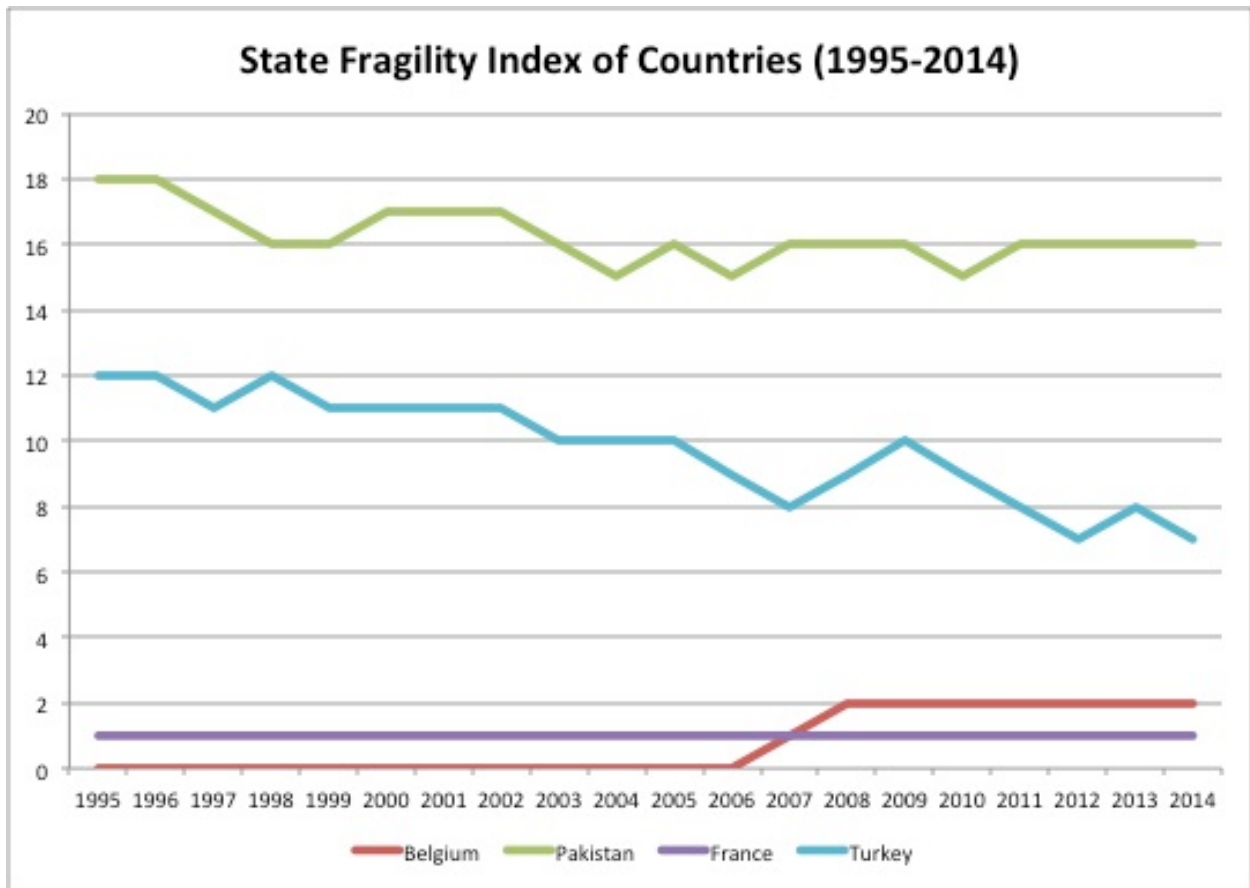
There are some limitations to this study that should be discussed, which can also be regarded as suggestions for future research. First, social media data only provides insights about Internet users. The results should be supported with data collected in conventional data collection methods. Secondly, the study mainly reflects the Western perspective because the comments that are analyzed are English and most of the Reddit users are from Western countries. Future studies can implement multilevel modeling, which may provide more insights on such a topic. In addition, studying other cases from other civilizations will surely take the scholarship on this issue further.

Figure 1. Total Number of Terrorism Incidents between 1968-2009



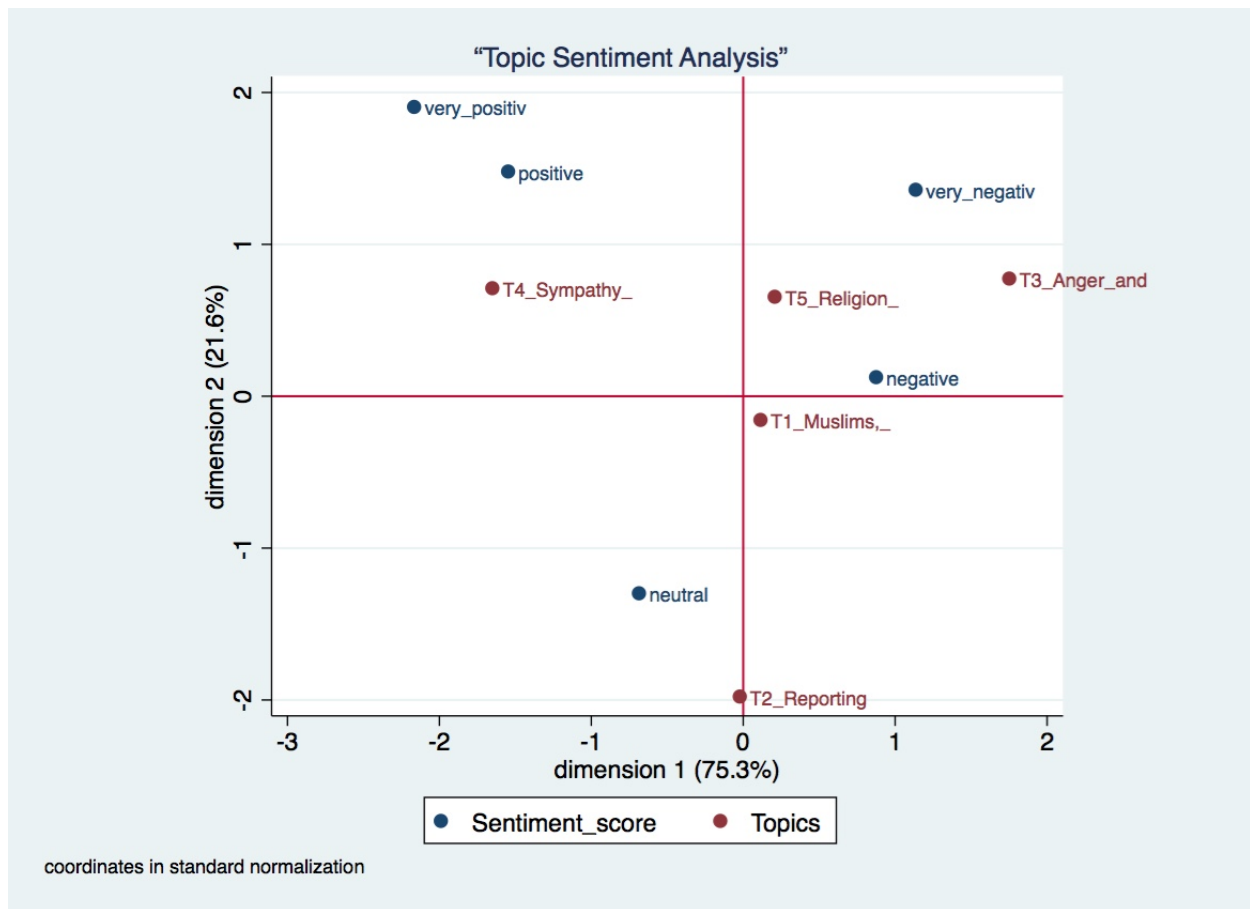
Data Sources: RAND Database of Worldwide Terrorism Incidents
OurWorldInData.org/terrorism/

Figure 2. State Fragility Index of France, Turkey, Belgium, and Paris (1995-2014)



Source: State Fragility Index, Center for Systemic Peace

Figure 3. Topic Sentiment Map



Headline	Newspaper
Where is Ankara's 'Je suis' moment?"	The Guardian
"You can't change you Facebook profile picture for Ankara because brown lives still aren't worth social media's grief"	Independent
"Nigeria's Horror in Paris's Shadow"	The Atlantic
"Facebook gets flak for Beirut-Paris 'double standard'"	Al Jazeera

ID	Place	Date	Terrorist Organization	Casualty	Reddit Comment Count
1	Paris, France	November 13, 2015	ISIS	130	28338
2	Ankara, Turkey	October 10, 2015	ISIS	103	1845
3	Brussels, Belgium	March 22, 2016	ISIS	32	20833
4	Lahore, Pakistan	March 27, 2016	Pakistani Taliban	75	5227

Table 3. Comparison of Four Countries of Interest					
ID	Place	State Fragility Index	Global Terrorism Index	Number of Internet Users	Civilization
1	France	34.5 (158th most fragile country)	4.553	55,860,330 (86.4%)	Western
2	Turkey	77.3 (79th)	5.737	46,196,720(58%)	Islamic
3	Belgium	29 (164th)	1.977	10,060,745 (88.5%)	Western
4	Pakistan	101.7 (14th)	9.065	34,342,400 (17.8%)	Islamic

Sources: Global Terrorism Index 2015, Institute for Economics and Peace
Fragile States Index 2016, The Fund for Peace
Internet Live Stats 2016, internetlivestats.com

Table 4. Distribution of Frequency for Commenters' Nationalities					
<i>Terrorist Attack</i>	Paris	Ankara	Brussels	Lahore	Total
<i>Nation of the commenters</i>					
American	32 (%64)	16 (%32)	32 (%64)	32 (%64)	112 (%56)
Turkish	-	18 (%36)	1 (%2)	-	19 (%9.5)
British	7 (%14)	2 (%4)	4 (%8)	3 (%6)	16 (%8)
Canadian	1 (%2)	3 (%6)	1 (%2)	5 (%10)	10 (%5)
French	2 (%4)	2 (%4)	-	2 (%4)	6 (%3)
German	1 (%2)	-	1 (%2)	-	2 (%1)
Australian	1 (%2)	-	2 (%4)	-	3 (%1.5)
Pakistani	-	-	-	3 (%6)	3 (%1.5)
Belgian			1 (%2)	-	1 (%0.5)
Indian				2 (%4)	2 (%1)
Singapore				1 (%2)	1 (%0.5)
Indonesian				1 (%2)	1 (%0.5)
Armenian				1 (%2)	1 (%0.5)
Norwegian	1 (%2)				1 (%0.5)
Spanish	2 (%4)				2 (%1)
Portuguese		2 (%4)			2 (%1)
Danish	1 (%2)	2 (%4)			3 (%1.5)
Bosnian		1 (%2)			1 (%0.5)
Swiss		1 (%2)			1 (%0.5)
Swedish	1 (%2)		1 (%2)		2 (%1)
Serbian		1 (%2)			1 (%0.5)
Iranian		1 (%2)			1 (%0.5)
Finnish			2 (%4)		2 (%1)
Dutch			3 (%6)		3 (%1.5)
Croatian			1 (%2)		1 (%0.5)
European ¹	1 (%2)	1 (%2)	1 (%2)		3 (%1.5)
Total	50 (%100)	50 (%100)	50 (%100)	50 (%100)	200 (%100)

Table 5. Topics, Terms and Number of Comments for Each Topic				
Topic	Label	Descriptive Terms	Number of Terms	Number of Comments
T1	Muslims, Refugees and Terrorism	-muslim, attack, terrorist, isis, europe, country, refugee, bomb, middle east, islamic, war, terror, border, world	190	2345
T2	Reporting the News	-report, dead, news, bataclan, hostage, explosion, police, concert, attack, hall, shoot, cnn, metro station	165	1597
T3	Anger and Cursing	-fuck, shit, people, holy, religion, terrorist, stop, islam, kill, isis, hell, world, coward, sick, stupid, piece	75	1373
T4	Sympathy for Paris	-France, safe, stay, paris, people, strong, hope, family, friend, right, heart, prayer, feel, love, help, live	163	1746
T5	Religion and Making Generalizations	-people, religion, islam, kill, muslim, christian, innocent, die, world, life, god, hate, extremist, problem	191	2285

Table 6. Descriptive Statistics of the Variables in the First Part of the Study				
Variable	Mean	SD	Min. Value	Max. Value
<i>Dependent Variable</i>				
Popularity score	.824	.64	0	2
<i>Independent Variables</i>				
Western ¹	.87	.33	0	1
Casualty	87.70	45.53	32	130
Sentiment	-.451	1.58	-20	7
<i>Interaction Variable</i>				
West x Casualty	77.34	53.96	0	130

¹<Non-Western> is the reference group

Source: Reddit Comments

N:5624

Table 7. Descriptive Statistics of the Variables in the Second Part of the Study				
Variable	Mean	SD	Min. Value	Max. Value
<i>Dependent Variable</i>				
Sentiment Score	-.451	1.58	-20	7
<i>Independent Variables</i>				
Muslims, Refugees and Terrorism (T1)*	.037	.057	-.10	.44
Reporting the News (T2)	.031	.059	-.07	.66
Anger and Cursing (T3)	.031	.061	0	.53
Sympathy for Paris (T4)	.030	.057	-.19	.4
Religion and Making Generalizations (T5)	.027	.054	-.12	.33

*The values for the topics show the factor loadings of topics for each comment.

Source: Reddit Comments

N:5624

Table 8. Ordinal Logistic Regression Analysis Estimates Predicting Popularity Score						
Variable	Model 1		Model 2		Model 3	
	B (SE)	Odds Ratio	B (SE)	Odds Ratio	B (SE)	Odds Ratio
<i>Independent Variables</i>						
Western ¹	.217** (.079)	1.242	.229** (.079)	1.257	.220** (.081)	1.246
Sentiment	-.035* (.017)	.965	-.034* (.017)	.966	-.001 (.018)	.999
<i>Control Variable</i>						
Casualty			-.002*** (.0006)	.998	-.002 ** (.001)	.998
<i>Topic Variables</i>						
Muslims, Refugees and Terrorism (T1)*					2.912*** (.471)	18.411
Reporting the News (T2)					-.527 (.458)	.590
Anger and Cursing (T3)					1.370** (.456)	3.935
Sympathy for Paris (T4)					1.544*** (.463)	4.683
Religion and Making Generalizations (T5)					1.953*** (.504)	7.049
-2log likelihood	11754.7		10743.5		10665.8	
Model χ^2	12.18		23.40		101.09	
Pseudo R ²	.011		.022		.094	
N	5624		5624		5624	

¹<Non-Western> is the reference group

*** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$ (two-tailed tests)

Notes: Standard errors are in parenthesis.

Source: Reddit comments

Table 9. OLS Regression Analysis Estimates Predicting Sentiment Scores		
Variable	B (SE)	β
Muslims, Refugees and Terrorism (T1)	-4.216*** (.340)	-.153
Reporting the News (T2)	-4.790*** (.335)	-.179
Anger and Cursing (T3)	-7.636*** (.320)	-.294
Sympathy for Paris (T4)	.863* (.342)	.031
Religion and Making Generalizations (T5)	-5.703** (.362)	-.196
Constant	.219 (.033)	
Model F		210.97
Model R ²		.1581
N		5624

*** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$ (two-tailed tests)

Notes: Standard errors are in parenthesis.

Source: Reddit comments

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