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## EMOTION DETECTION ON KENYAN TWEETS USING EMOTION ONTOLOGY

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### Abstract

**Purpose:** The purpose of the study was emotion detection on Kenyan tweets as a powerful tool in detecting and recognizing the various feelings among netizens and provide critical analytics that can be used in various platforms for decision making.

**Methodology:** This research study adopted a descriptive research design approach. The researcher preferred this method because it allowed an in-depth study of the subject. The target population will be twitter account holders with twitter followers ranging between 100,000 up to 2000, 000 in Kenya. Data was analyzed using descriptive and inferential statistics. The study will employ a census approach to collect data from the respondents hence no sampling techniques will be used. According to Larry (2013) a census is a count of all the elements in a population. The sample size will be the 150 respondents .Quantitative data was analyzed using multiple regression analysis. The qualitative data generated was analyzed by use of Statistical Package of Social Sciences (SPSS) version 20.

**Results:** The response rate of the study was 64%.The findings of the study indicated that hashtags, emojis, GIF's and adjectives have a positive relationship with emotion detection in Kenya.

**Conclusion:** R square value of 0.715 means that 71.5% of the corresponding categorization in emotion ontology can be explained or predicted by (hashtags, emojis, GIF's and adjectives) which indicated that the model fitted the study data. The results of regression analysis revealed that there was a significant positive relationship between dependent variable and independent variable at ( $\beta = 0.715$ ),  $p=0.000 < 0.05$ ).

**Policy recommendation:** Finally, the study recommended that twitter account holders should embrace various emotion detecting platforms so as to improve how they articulate issues and further researches should to be carried out in other social media platforms to find out if the same results can be obtained.

**Keywords:** *hash tag, emoji, GIF's, adjective, emotion ontology*

## **1.0 INTRODUCTION**

### **1.1 Background of the Study**

Human has ability to see emotions by temperament, disposition, personality and mood. Computer seeks to emulate the human emotions by digital image analysis. The problem with the computer vision is due to the fact that world is three dimensional but computer has only two dimensions (Collins, 2015). In our day to day life we interact with each other directly (for e.g. face to face) or indirectly (for e.g. phone calls). In some profession interaction like call centers interaction with people is important. With great advancement in technology in terms of different techniques of people interacting with each other it is quite necessary that one should be aware of current emotions of the person he/she is interacting. It is widely accepted from psychological theory that human emotions can be classified into six archetypal emotions: love, surprise, fear, anger, joy, and sadness. Facial motion and the tone of the speech play a major role in expressing these emotions (Evans, 2012).

#### **1.1.1 Global Perspective**

According to a study done by Paek and Pan (2014) recognizing the emotion of the online text plays a key role in the human-computer interaction. Emotions may be expressed by a person's speech, face expression and written text known as speech, facial and text based emotion respectively. Sufficient amount of work has been done regarding to speech and facial emotion recognition but online text based emotion recognition system still needs attraction of researchers. In computational linguistics, the detection of human emotions in text is becoming increasingly important from an applicative point of view (Noor Al-Deen & Hendricks, 2013).

#### **1.1.2 Regional Perspective**

According to Tungate (2012) in a study done in South Africa, emotion detection is a natural language processing and text mining that automatically discover people's emotion from textual data such as tweet. Tweet is information updated by a user in Twitter personal micro blog, no longer than 140 characters for networking among followers. Although the status update of users are a brief text, tweet is updated hundreds of millions of times a day by people all over the world and its content varies tremendously based on user interests and behaviors. Users express their emotions as a response of an event and status through the broadcast post.

#### **1.1.3 Local Perspective**

For a long time, Kenyans have relied on their country's well-developed mainstream media for information. Recently however, more and more Kenyans have begun turning to social media for quick and frequently updated news (Njoroge, 2013). As such, journalists and professional media houses have embraced the use of social media for news sourcing and dissemination of information in order to remain relevant. Social media has various advantages including speed of accessing and disseminating information, ease of updating unfolding stories, providing a forum for discussions, among others. Amid these benefits, there are various challenges that journalists and other social media users face (Madowo, 2015).

## 1.2 Problem Statement

According to a report by the World Bank (2010) Kenya is embracing social media as a tool to disseminate information thus everyone has the potential to be watchdog, citizen journalist and photo journalist and constantly survey the world around them and share what they source online. This acceleration of communication and awareness has serious implications for crisis communications. It is changing the landscape in which crisis communicators operate (KIPPR, 2013). Social media in Kenya has become a great resource in times of crisis. It provides tools for communities to crowd source real time information using text messages, emails and social networks (Deloitte, 2012).

For example, Kenyan bloggers, Robert Alai, Cyprian Nyakundi, Juliana Rotich and David Kobia, developed a journalistic platform that would allow the public to share information using the available communication means (social media). The crowd-sourcing platform was called “Ushahidi”, which means “testimony” in Kiswahili; it was a way for the public to share their views regarding general post-election violence of 2007/2008. Ushahidi was used to get citizens’ testimonies using social media for example, Twitter, and blogs. At that point, Kenya’s online community collaborated and shared content, depending on their location (Madowo, 2015).

Groups organizing through online platforms have done so without fear of being subverted and prosecuted by state security apparatus and authorities (CCG, 2010). They have also been able to mobilize without traditional modes of support, including the conventional media. For instance, Bunge la Mwananchi Movement (“People’s Parliament”) utilizes three Twitter pages to mobilize citizens’ opinions on governance and has a following of over 50,000 people. The emerging trends of social media have greatly impacted the dissemination of information developed. Kenyan media have not been left behind in technological convergence (OECD, 2012).

Media have become receivers of content from the public, a shift from its previous role as disseminators of news and information. Audiences are invading an arena that has been the preserve of journalists (Transparency International, 2010). What’s more, people have realized the importance of adopting an intelligent curiosity mindset, where they challenge what is presented before them, all these developments signal, is a new era of media consumers and creators, that are heavily involved in the process of information gathering and sharing. Over the past few years social media has emerged as a very powerful frontier for mass communication compared to other online platforms. This is especially in regard to active use of social media (USAID, 2012).

Several studies have been done; Ochman (2012) interrogated why twitter was a better platform than facebook, while Enge (2014) assessed twitter engagement by studying emotions among tweets in Uganda. These studies have been done in other countries and very few if any have been done in Kenya. It is against this back drop that this study seeks to assess emotion detection on Kenyan tweets using emotion ontology.

### 1.3 Objectives of the Study

- i. To assess the category of a Kenyan tweet hash tag using emotion ontology.
- ii. To establish the classification of a Kenyan tweet emoji using emotion ontology.
- iii. To determine the category of a Kenyan tweet GIF using emotion ontology.
- iv. To evaluate the classification of a Kenyan tweet adjective using emotion ontology.

## 2.0 LITERATURE REVIEW

### 2.1.1 Hash tags

Lanham (2016) has addressed our recent cultural shift from an economy of goods to an economy of information, arguing that because we are inundated with information, the ability to garner attention holds significant value. While Lanham positions style as the new currency in this information economy, Twitter a platform on which a thousand followers is not unusual demonstrates how attention is increasingly perceived in quantitative terms. For some, the attention that #yesallwomen received, measured in tweets and retweets, became a threatening commodity (Madge & Hooley, 2009).

### 2.1.2 Emojis

Previous work on emojis mainly focuses on three research directions: the meanings and sentiments of emojis, as well as the different usages of emojis among people. The technical report of Instagram is the first attempt to study the meaning of emojis using a word embedding approach (Dimson 2015). In the work, the authors vectorized the emojis occurred in Instagram posts, and used the semantically closest words to the emojis in the vector space as their explanations (Boyd & Ellison, 2008).

Eisner *et al.*, (2016) also proposed an embedding model – emoji2vec – to learn emoji representations (Eisner *et al.*, 2016). Instead of learning the emoji vectors from social media posts, they leveraged the emoji descriptions, and reported better performances on evaluation tasks. Similarly, Wijeratne *et al.*, (2011) set up a machine readable sense inventory for emoji by aggregating the explanations of emojis from multiple online sources (Wijeratne *et al.*, 2011).

### 2.1.3 Graphic Interchange Formats

In the study of Maruya *et al.*, (2016), it was concluded that using a visual stimulus was found to have a significant effect. Animation presentation was found to provide understanding of information and to facilitate learning. Animations must be slow and clear enough for observers to perceive movements, changes, and their timing, and to understand the changes in relations between the parts and the sequence of events (Tversky *et al.*, 2012).

In their study, Bulbul and Ilgun (2015) showed 20 Animated GIFs to 75 teacher candidates and identified some GIFs as adequate and others as inadequate. Being incomparable, lack of clarity, faintness, not having a purpose, not being interesting, lack of information, discoloration, unnecessary drawing, not using three-dimensional drawing, uneven size or smallness, amateurism of drawings were identified as causes of visual inadequacy.

For educational inadequacy, lack of information, being too fast, inappropriate level, wrong information, missing explanation, wrong arrangement, lack of detail, not being catchy, not being fit for every situation, not-being provided in a known context, and foreign words were prominent causes of inadequacy. When these inadequacies were evaluated, not being clear, discoloration, being confusing, not being attention grabbing, and being too fast were specified for visual inadequacies; while not being at the appropriate level, not being focused, lack of detail, not having a purpose, insufficient duration, wrong information and missing information were brought forward as causes of educational inadequacy (Njoroge, 2013).

#### **2.1.4 Adjectives**

According to Barbieri *et al.*, (2016), in his study opines that this methodology of selecting tweets has been applied within a variety of other disaster events, using the same technique to select tweets containing key words relevant to the 2009 Oklahoma fires, such as ‘Oklahoma’, ‘grassfire’ and ‘OKfire’, in order to study retweeting conventions during mass emergencies. Others utilize tweets containing the hashtag ‘#qldfloods’ to analyse the 2011 flooding event in Queensland, Australia. Similar studies analyse two separate hurricane events by utilizing tweets containing the word ‘hurricane’ as well as the respective hurricane names.

However, the methodology described generates several issues which severely hamper the results of these studies. Perhaps most critically, following tweets containing only a select set of words means that many other tweets relevant to the disaster event are missed out entirely from the study. Additionally, the choice of words to follow is subjective based on the authors’ perception of the event.

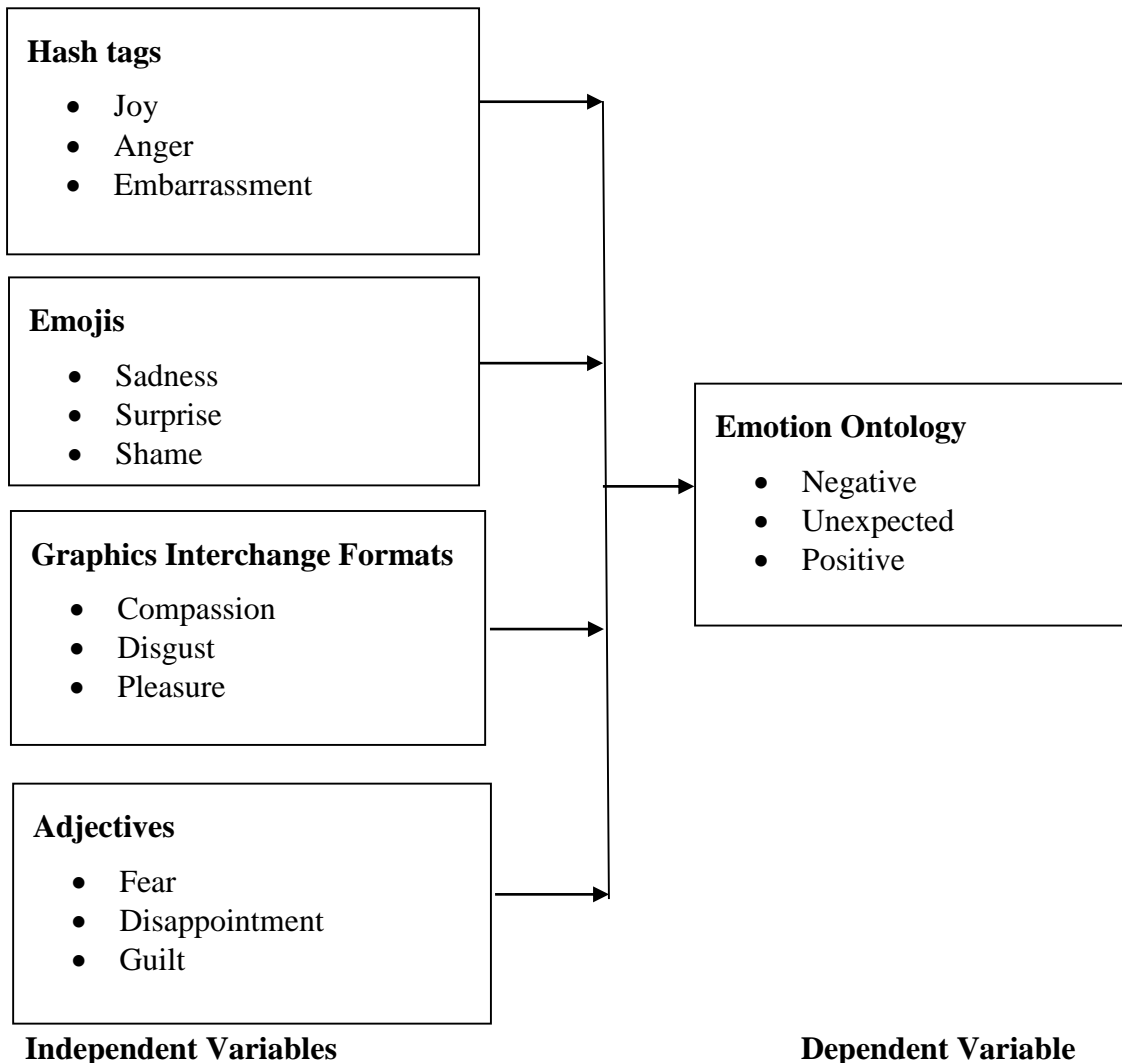
### **2.2 Theoretical review**

#### **2.2.1 Technology Acceptance Model**

The first theory; Fred Harris’ Technology Acceptance Model (TAM) of 1985; explains the use of technology; in this case, social media as a form of technology. Technology enabled social interaction processes, such as everyday interaction, sharing photo, presentation of self, etc., on social media sites (Raniar, 2014). The widespread popularity of these social media sites suggests that these online technologies are successful because of the acceptance and usage in the personal, social, and professional life of individual users.

If this means that it is primarily voluntary, then the causes of these behaviors have to be rooted in personal intentions and motives. In his proposal, Davis (1985) suggested that users’ motivation be explained by three factors: perceived ease of use, perceived usefulness, and attitude towards using the system. Chuttur (2009) explains Davis’ hypothesis that the attitude of a user toward a system is a major determinant of whether the user will actually use or reject the system.

### 2.3 Conceptual Framework



**Figure 1: Conceptual Framework**

### 3.0 METHODOLOGY

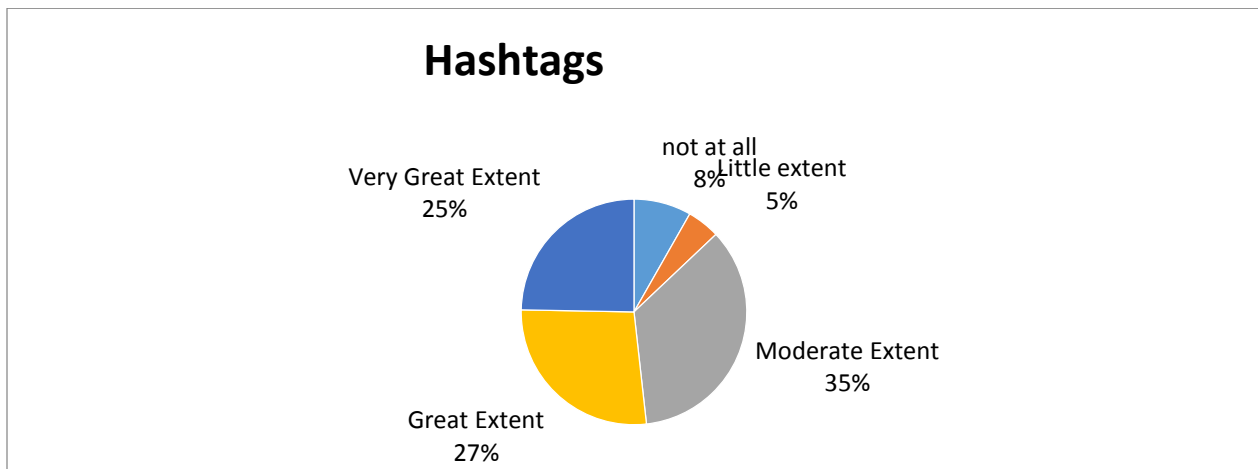
This research study adopted a descriptive research design approach. The researcher preferred this method because it allowed an in-depth study of the subject. The target population will be twitter account holders with twitter followers ranging between 100,000 up to 2000, 000 in Kenya. Data was analyzed using descriptive and inferential statistics. The study will employ a census approach to collect data from the respondents hence no sampling techniques will be used. According to Larry (2013) a census is a count of all the elements in a population. The sample size will be the 150 respondents. Quantitative data was analyzed using multiple regression analysis. The qualitative data generated was analyzed by use of Statistical Package of Social Sciences (SPSS) version 20.

## 4. 0 RESULTS FINDINGS

### 4.1 Descriptive Statistics

#### 4.1.1 Hashtags

The first objective of the study was to assess the category of a Kenyan tweet hash tag using emotion ontology. The respondents were asked to indicate to what extent a hashtag helped to indicate the category it belonged. Results indicated that majority of the respondents 25% agreed that it was to a very great extent, 27% said that it was to a great extent, 35% said it was moderate, while little extent and not all were at 5 and 8% respectively.



**Figure 2: Hashtags**

The respondents were also asked to comment on statements regarding hashtags and their category under emotion ontology. The responses were rated on a likert scale and the results presented in table 1 below. It was rated on a 5 point likert scale ranging from; 1 = strongly disagree to 5 = strongly agree. The scores of 'strongly disagree' and 'disagree' have been taken to represent a statement not agreed upon, equivalent to mean score of 0 to 2.5. The score of 'neutral' has been taken to represent a statement agreed upon, equivalent to a mean score of 2.6 to 3.4. The score of 'agree' and 'strongly agree' have been taken to represent a statement highly agreed upon equivalent to a mean score of 3.5 to 5.

The respondents were asked to indicate their descriptive responses for hashtags. The result revealed that majority of the respondent with a mean of (4.3) agreed with the statement that a joyous hash tag significantly influences if it belongs to the negative side of the ontology. The measure of dispersion around the mean of the statements was 1 indicating the responses were varied. The result revealed that majority of the respondent with a mean of (3.6) agreed with the statement that an anger filled hash tag significantly influences if it belongs to the negative side of the ontology. The measure of dispersion around the mean of the statements was 1.4 indicating the responses were varied.



The result revealed that majority of the respondent with a mean of (3.8) agreed with the statement that an embarrassment hash tag significantly influences if it belongs to the negative side of the ontology. The measure of dispersion around the mean of the statements was 1.3 indicating the responses were varied.

The result revealed that majority of the respondent with a mean of (3.0) agreed with the statement that a joyous hash tag significantly influences if it belongs to the unexpected side of the ontology. The measure of dispersion around the mean of the statements was 1.4 indicating the responses were varied. The result in table 4.5.1 revealed that majority of the respondent with a mean of (4.2) agreed with the statement that an anger filled hash tag significantly influences if it belongs to the unexpected side of the ontology. The measure of dispersion around the mean of the statements was 1 indicating the responses were varied. The result revealed that majority of the respondent with a mean of (3.7) agreed with the statement that an embarrassment hash tag significantly influences if it belongs to the unexpected side of the ontology. The measure of dispersion around the mean of the statements was 1 indicating the responses were varied.

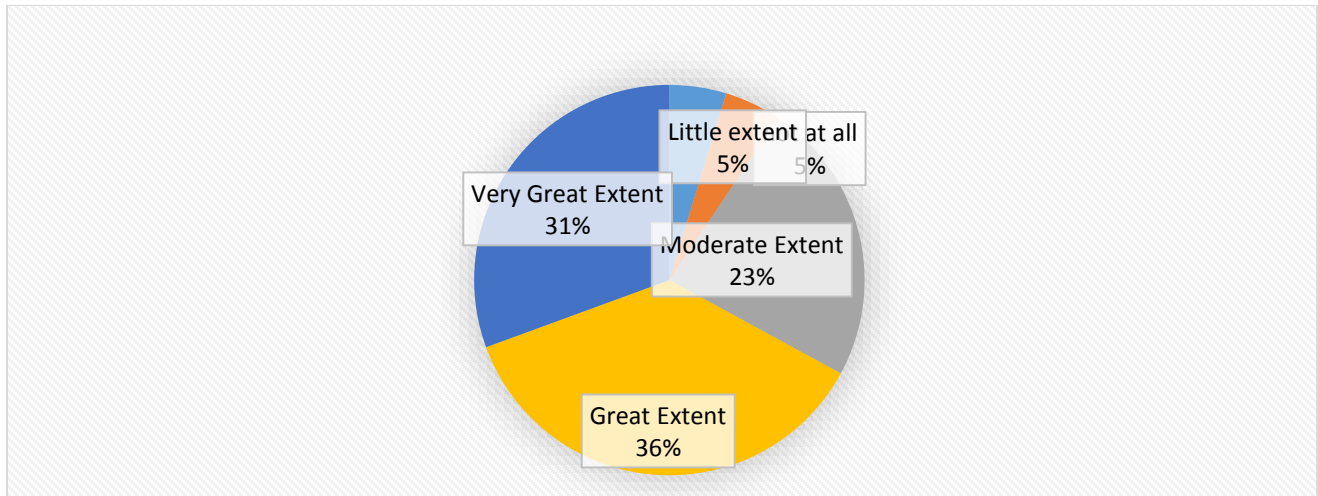
The result revealed that majority of the respondent with a mean of (3.4) agreed with the statement that a joyous hash tag significantly influences if it belongs to the positive side of the ontology. The measure of dispersion around the mean of the statements was 1.3 indicating the responses were varied. The result revealed that majority of the respondent with a mean of (3.8) agreed with the statement that an anger filled hash tag significantly influences if it belongs to the positive side of the ontology. The measure of dispersion around the mean of the statements was 1.2 indicating the responses were varied. The result revealed that majority of the respondent with a mean of (3.8) agreed with the statement that an embarrassment hash tag significantly influences if it belongs to the positive side of the ontology. The measure of dispersion around the mean of the statements was 1.2 indicating the responses were varied. However the variations in the responses were varied as shown by an average standard deviation of 1.5 and an average mean of 3.8. The findings agree with Knudsen (2015) that using emotion ontology one can establish the category of a hashtag.

**Table 1: Hashtags**

Statements	N	Me an	Std. Deviation
A joyous hash tag significantly influences if it belongs to the negative side of the ontology	96	4.3	1.0
An anger filled hash tag significantly influences if it belongs to the negative side of the ontology	96	3.6	1.4
An embarrassment hash tag significantly influences if it belongs to the negative side of the ontology	96	3.8	1.3
A joyous hash tag significantly influences if it belongs to the unexpected side of the ontology	96	3.0	1.4
An anger filled hash tag significantly influences if it belongs to the unexpected side of the ontology	96	4.2	1.0
An embarrassment hash tag significantly influences if it belongs to the unexpected side of the ontology	96	3.7	0.5
A joyous hash tag significantly influences if it belongs to the positive side of the ontology	96	3.4	1.3
An anger filled hash tag significantly influences if it belongs to the positive side of the ontology	96	4.1	4.3
An embarrassment hash tag significantly influences if it belongs to the positive side of the ontology	96	3.8	1.2
Average	96	3.8	1.5

#### 4.1.2 Emojis

The second objective of the study was to establish the classification of a Kenyan tweet emoji using emotion ontology. The respondents were asked to indicate to what extent an emoji helped to indicate the category it belonged. Results indicated that majority of the respondents 31% agreed that it was to a very great extent, 36% said that it was to a great extent, 23% said it was moderate, while little extent and not all tied at 5%.



**Figure 3: Emojis**

The respondents were also asked to comment on statements regarding emojis. The respondents were asked to indicate descriptive responses for emojis. The result revealed that majority of the respondents as indicated by a mean of (3.8) indicated that they agreed with the statement that a sad emoji significantly influences if it belongs to the negative side of the ontology. The responses were varied as measured by standard deviation of 1.1. The result revealed that majority of the respondents as indicated by a mean of (3.6) indicated that they agreed with the statement that a surprise emoji significantly influences if it belongs to the negative side of the ontology. The responses were varied as measured by standard deviation of 1.1. The result revealed that majority of the respondents as indicated by a mean of (3.7) indicated that they agreed with the statement that a shameful emoji significantly influences if it belongs to the negative side of the ontology. The responses were varied as measured by standard deviation of 1.1

The result revealed that majority of the respondents as indicated by a mean of (3.6) indicated that they agreed with the statement that a sad emoji significantly influences if it belongs to the unexpected side of the ontology. The responses were varied as measured by standard deviation of 1.2. The result revealed that majority of the respondents as indicated by a mean of (3.6) indicated that they agreed with the statement that a surprise emoji significantly influences if it belongs to the unexpected side of the ontology. The responses were varied as measured by standard deviation of 1.2. The result revealed that majority of the respondents as indicated by a mean of (3.5) indicated that they agreed with the statement that a shameful emoji significantly influences if it belongs to the unexpected side of the ontology. The responses were varied as measured by standard deviation of 1.4.

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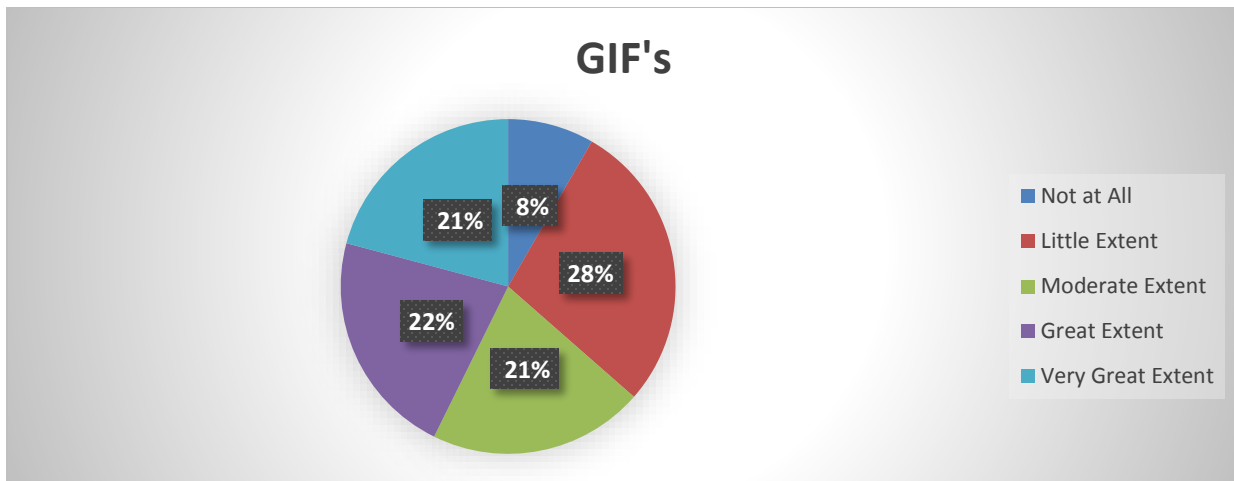
The result revealed that majority of the respondents as indicated by a mean of (3.6) indicated that they agreed with the statement that a shameful emoji significantly influences if it belongs to the positive side of the ontology. The responses were varied as measured by standard deviation of 0.5. However the variations in the responses were varied as shown by an average standard deviation of 1.2 and an average mean of 3.6. The findings agree with Lysons (2013) that using emotion ontology one can establish the category of an emoji.

**Table 2: Emojis**

Statements	N	Mean	Std. Deviation
A sad emoji significantly influences if it belongs to the negative side of the ontology	96	3.8	1.1
A surprise emoji significantly influences if it belongs to the negative side of the ontology	96	3.6	1.1
A shameful emoji significantly influences if it belongs to the negative side of the ontology	96	3.7	1.1
A sad emoji significantly influences if it belongs to the unexpected side of the ontology	96	3.5	1.2
A surprise emoji significantly influences if it belongs to the unexpected side of the ontology	96	3.8	1.2
A shameful emoji significantly influences if it belongs to the unexpected side of the ontology	96	3.5	1.4
A sad emoji significantly influences if it belongs to the positive side of the ontology	96	3.5	1.4
A surprise emoji significantly influences if it belongs to the positive side of the ontology	96	3.3	1.5
A shameful emoji significantly influences if it belongs to the positive side of the ontology	96	3.6	0.5
Average	96	3.6	1.2

#### 4.1.3 Graphic Interchange Formats

There was also need to determine the category of a Kenyan tweet GIF using emotion ontology. The respondents were asked to comment on extent did a GIF help to indicate the category it belonged. Results indicated that majority of the respondents 21% agreed that it was to a very great extent, 22% said that it was to a great extent, 21% said it was moderate; little extent was 28% and not all at 8%.



**Figure 4: GIF's**

The respondents were asked to indicate their levels of agreement on statements regarding GIF's. The results revealed that majority of the respondent (3.9) agreed with the statement that a compassionate GIF significantly influences if it belongs to the negative side of the ontology. The responses were varied as shown by the standard deviation of 1.2. The results revealed that majority of the respondent (3.2) agreed with the statement that a disgustful GIF significantly influences if it belongs to the negative side of the ontology. The responses were varied as shown by the standard deviation of 1.3. The results revealed that majority of the respondent (4.0) agreed with the statement that a pleasurable GIF significantly influences if it belongs to the negative side of the ontology. The responses were varied as shown by the standard deviation of 0.8.

The results revealed that majority of the respondent (4.2) agreed with the statement that a compassionate GIF significantly influences if it belongs to the unexpected side of the ontology. The responses were varied as shown by the standard deviation of 0.9. The results revealed that majority of the respondent (3.7) agreed with the statement that a disgustful GIF significantly influences if it belongs to the unexpected side of the ontology. The responses were varied as shown by the standard deviation of 0.5. The results revealed that majority of the respondent (2.4) agreed with the statement that a pleasurable GIF significantly influences if it belongs to the unexpected side of the ontology. The responses were varied as shown by the standard deviation of 1.3.

The results revealed that majority of the respondent (3.1) agreed with the statement that a compassionate GIF significantly influences if it belongs to the positive side of the ontology. The responses were varied as shown by the standard deviation of 1.2. The results revealed that majority of the respondent (3.2) agreed with the statement that a disgustful GIF significantly influences if it belongs to the positive side of the ontology. The responses were varied as shown by the standard deviation of 1.3. The results revealed that majority of the respondent (3.5) agreed with the statement that a pleasurable GIF significantly influences if it belongs to the positive side of the ontology. The responses were varied as shown by the standard deviation of 1.3.

The average mean of all the statements was 3.7, however the variations in the responses were varied as shown by a standard deviation of 1.1. These findings imply that one can use emotion ontology to determine the category of a GIF's (Maina, 2008).

**Table 3: GIF's**

Statements	N	Mean	Std. Deviation
A compassionate GIF significantly influences if it belongs to the negative side of the ontology	96	3.9	1.2
A disgustful GIF significantly influences if it belongs to the negative side of the ontology	96	3.2	1.3
A pleasurable GIF significantly influences if it belongs to the negative side of the ontology	96	4.0	0.8
A compassionate GIF significantly influences if it belongs to the unexpected side of the ontology	96	4.2	0.9
A disgustful GIF significantly influences if it belongs to the unexpected side of the ontology	96	3.7	0.5
A pleasurable GIF significantly influences if it belongs to the unexpected side of the ontology	96	2.4	1.3
A compassionate GIF significantly influences if it belongs to the positive side of the ontology	96	3.1	1.2
A disgustful GIF significantly influences if it belongs to the positive side of the ontology	96	3.2	1.3
A pleasurable GIF significantly influences if it belongs to the positive side of the ontology	96	3.5	1.3
Average	96	3.7	1.1

#### 4.1.4 Adjectives

There was also need to evaluate the classification of a Kenyan tweet adjective using emotion ontology. The respondents were also asked to comment on statements regarding adjectives. Results also showed that 3% of respondents indicated to very great extent, great extent was at 12%, moderate extent was 37%, while little extent was at 27% and not at all was at 21%.



**Figure 5: Adjectives**

The respondents were asked to indicate the descriptive responses for adjectives. The result revealed that majority of the respondent (3.2) agreed with the statement that a fearful adjective significantly influences if it belongs to the negative side of the ontology. The responses were varied as shown by a standard deviation of 1.3. The result revealed that majority of the respondent (3.2) agreed with the statement that a disappointed adjective significantly influences if it belongs to the negative side of the ontology. The responses were varied as shown by a standard deviation of 1. The result revealed that majority of the respondent (4.3) agreed with the statement that a guilty adjective significantly influences if it belongs to the negative side of the ontology. The responses were varied as shown by a standard deviation of 1.

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The result revealed that majority of the respondent (4.4) agreed with the statement that a fearful adjective significantly influences if it belongs to the positive side of the ontology. The responses were varied as shown by a standard deviation of 0.6. The result revealed that majority of the respondent (4.4) agreed with the statement that a disappointed adjective significantly influences if it belongs to the positive side of the ontology. The responses were varied as shown by a standard deviation of 0.6. The result revealed that majority of the respondent (4.4) agreed with the statement that a guilty adjective significantly influences if it belongs to the positive side of the ontology. The responses were varied as shown by a standard deviation of 0.7. The average mean response for the statements on electronic sourcing was 4.4, the variations in the responses was 0.9. The results imply that one can deduce the category of an adjective using emotion ontology (Bird, 2009).

**Table 4: Adjective**

Statements	N	Mean	Std. Deviation
A fearful adjective significantly influences if it belongs to the negative side of the ontology	96	3.2	1.3
A disappointed adjective significantly influences if it belongs to the negative side of the ontology	96	2.9	1.0
A guilty adjective significantly influences if it belongs to the negative side of the ontology	96	4.3	0.9
A fearful adjective significantly influences if it belongs to the unexpected side of the ontology	96	4.3	0.9
A disappointed adjective significantly influences if it belongs to the unexpected side of the ontology	96	4.1	1.0
A guilty adjective significantly influences if it belongs to the unexpected side of the ontology	96	4.2	0.8
A fearful adjective significantly influences if it belongs to the positive side of the ontology	96	4.4	0.6
A disappointed adjective significantly influences if it belongs to the positive side of the ontology	96	4.4	0.7
A guilty adjective significantly influences if it belongs to the positive side of the ontology	96	4.4	0.6
Average	96	4.4	0.9



## 4.2 Correlation Analysis

**Table 5: Summary of Pearson's Correlations**

Correlations		Hashtags	Emojis	GIF's	Adjectives	Emotion Ontology
Hashtags	Pearson Correlation	1				
	Sig. (2-Tailed)					
Emojis	Pearson Correlation	.372**	1			
	Sig. (2-Tailed)	0				
GIF's	Pearson Correlation	.353**	.449**	1		
	Sig. (2-Tailed)	0	0			
Adjectives	Pearson Correlation	.363**	.771**	.547**	1	
	Sig. (2-Tailed)	0	0	0		
Emotion Ontology	Pearson Correlation	.556**	.662**	.703**	.691**	1
	Sig. (2-Tailed)	0	0	0	0	

**\*\* Correlation is Significant at the 0.05 Level (2-Tailed).**

The correlation summary shown in Table 5 indicated that the associations between each of the independent variables and the dependent variable were all significant at the 95% confidence level. The correlation analysis to determine assess the category of a Kenyan tweet hash tag using emotion ontology, Pearson correlation coefficient computed and tested at 5% significance level. The results indicate that there was a positive relationship ( $r=0.556$ ) between a Kenyan tweet hash tag and emotion ontology category. In addition, the researcher found the relationship to be statistically significant at 5% level ( $p=0.000$ ,  $<0.05$ ).

The correlation analysis to determine the relationship between a Kenyan tweet emoji and emotion ontology category, Pearson correlation coefficient computed and tested at 5% significance level. The results indicated that there was a positive relationship ( $r=0.662$ ) between a Kenyan tweet emoji and emotion ontology category. In addition, the researcher found the relationship to be statistically significant at 5% level ( $p=0.000$ ,  $<0.05$ ).

The correlation analysis to determine the relationship between a Kenyan tweet GIF and emotion ontology category, Pearson correlation coefficient computed and tested at 5% significance level.

The results indicate that there was a positive relationship ( $r=0.703$ ) between a Kenyan tweet GIF and emotion ontology category. In addition, the researcher found the relationship to be statistically significant at 5% level ( $p=0.000, <0.05$ ).

The correlation analysis to determine the relationship between a Kenyan tweet adjective and emotion ontology category, Pearson correlation coefficient computed and tested at 5% significance level. The results indicate that there was a positive relationship ( $r=.691$ ) between a Kenyan tweet adjective and emotion ontology category. In addition, the researcher found the relationship to be statistically significant at 5% level ( $p=0.000, <0.05$ ). Hence, it was evident that all the independent variables could explain to which emotion ontology they belong, on the basis of the correlation analysis.

### 4.3 Regression Analysis

In this study multivariate regression analysis was used to determine the significance of the relationship between the dependent variable and all the independent variables pooled together. Regression analysis was conducted to find the proportion in the dependent variable (category of emotion ontology) which can be predicted from the independent variables (hashtags, emojis, GIF's and adjectives).

Table 6 presented the regression coefficient of independent variables against dependent variable. The results of regression analysis revealed there was a significant positive relationship between dependent variable and the independent variable. The independent variables reported R value of 0.846 indicating that there was perfect relationship between dependent variable and independent variables. R square value of 0.715 means that 71.5% of the corresponding categorization in emotion ontology can be explained or predicted by (hashtags, emojis, GIF's and adjectives) which indicated that the model fitted the study data. The results of regression analysis revealed that there was a significant positive relationship between dependent variable and independent variable at ( $\beta = 0.715$ ),  $p=0.000 <0.05$ ).

**Table 6: Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.846 <sup>a</sup>	.715	.703	.14869

a) Predictors: (Constant), Hashtags, Emojis, GIF's and Adjectives

b) Dependent Variable: Emotion Ontology

**Table 7: ANOVA**

Model		Sum Squares	of df	Mean Square	F	Sig.
1	Regression	5.002	4	1.251	56.562	.000 <sup>b</sup>
	Residual	1.99	91	0.022		
	Total	6.992	95			

a) Predictors: (Constant), Hashtags, Emojis, GIF's and Adjectives

b) Dependent Variable: Emotion Ontology

The significance value is 0.000 which is less than 0.05 thus the model is statistically significant in determining how hashtags, emojis, GIF's and adjectives help to categorise emotions. The F critical at 5% level of significance was 28.61. Since F calculated which can be noted from the ANOVA table above is 56.562 which is greater than the F critical (value= 28.61), this shows that the overall model was significant. The study therefore establishes that; hashtags, emojis, GIF's and adjectives were all important emotion detectors helping to categorize emotions. These results agree with Odhiambo and Kamau (2013) results which indicated a positive and significant relationship between using emotion detectors such as hashtags, emojis, GIF's and adjectives to determine the category of the emotion.

**Table 8: Coefficients of Determination**

Model		Unstandardized		Standardized	t	Sig.
		Coefficients				
		B	Std. Error	Beta		
1	(Constant)	2.07	0.193		10.725	0.000
	Hashtags	0.166	0.041	0.255	4.048	0.000
	Emojis	0.138	0.053	0.235	2.603	0.010
	GIF's	0.119	0.021	0.398	5.667	0.000
	Adjectives	0.09	0.043	0.201	2.093	0.037

a) Predictors: (Constant), Hashtags, Emojis, GIF's and Adjectives

b) Dependent Variable: Emotion Ontology

The research used a multiple regression model

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \epsilon$$

The regression equation will be;

$$Y=2.07+ 0.166X_1 + 0.138X_2 + 0.119X_3 + 0.09X_4$$

The regression equation above has established that taking all factors into account (hashtags, emojis, GIF's and adjectives) constant at zero, emotion ontology in Kenya will be an index of 2.07. The findings presented also shows that taking all other independent variables at zero, a unit increase in using hashtags will lead to a 0.166 increase in categorising an emotion. The P-value was 0.000 which is less 0.05 and thus the relationship was significant.

The study also found that a unit increase in using emojis will lead to a 0.138 increase in categorising an emotion. The P-value was 0.00 and thus the relationship was significant. In addition, the study found that a unit increase in using GIF's will lead to a 0.119 increase in categorising an emotion. The P-value was 0.000 and thus the relationship was significant.

Lastly, the study found that a unit increase in using adjectives will lead to a 0.09 increase in categorising an emotion. The P-value was 0.00 and hence the relationship was significant since the p-value was lower than 0.05. The findings of the study show that, hashtags contributed most to emotion detection and categorization.

## **5. 0 SUMMARY, CONCLUSION AND RECOMMENDATIONS**

### **5.1 Summary of Findings**

#### **5.1.1 Hashtags**

The study sought to assess the category of a Kenyan tweet hash tag using emotion ontology as the first objective of the study. A majority of respondents were found to highly agree that twitter account holders had embraced hashtags with regard to their tweets. Expressing joy and anger using hashtags was common in twitter. Correlation and regression results revealed that this was an important variable that could perhaps be explained by the observation from the findings that hashtags were an important factor in determining the category of an emotion.

#### **5.1.2 Emojis**

The study sought to establish the classification of a Kenyan tweet emoji using emotion ontology as the second objective of the study. A majority of respondents were found to highly agree that twitter account holders had embraced emojis with regard to their tweets. Expressing sadness and shame using emojis was common in twitter. Correlation and regression results revealed that this was an important variable that could perhaps be explained by the observation from the findings that emojis an important factor in determining the category of an emotion.

#### **5.1.3 Graphics Interchange Formats**

The study endeared to determine the category of a Kenyan tweet GIF using emotion ontology as the third objective of the study. A majority of respondents were found to highly agree that twitter account holders had embraced GIF's with regard to their tweets. Expressing disgust and pleasure using emojis was common in twitter. Correlation and regression results revealed that this was an important variable that could perhaps be explained by the observation from the findings that GIF's was an important factor in determining the category of an emotion.

### 5.2.4 Adjectives

The study sought to evaluate the classification of a Kenyan tweet adjective using emotion ontology as the last objective of the study. A majority of respondents were found to highly agree twitter account holders had embraced adjectives with regard to their tweets. Expressing fear and disappointment using adjectives was common in twitter. Correlation and regression results revealed that this was an important variable that could perhaps be explained by the observation from the findings that adjectives was an important factor in determining the category of an emotion.

### 5.2 Conclusion of the Study

R square value of 0.715 means that 71.5% of the corresponding categorization in emotion ontology can be explained or predicted by (hashtags, emojis, GIF's and adjectives) which indicated that the model fitted the study data. The results of regression analysis revealed that there was a significant positive relationship between dependent variable and independent variable at ( $\beta = 0.715$ ),  $p=0.000 <0.05$ ).

### 5.3 Recommendations of the Study

The study recommended that twitter account holders should embrace various emotion detecting platforms so as to improve how they articulate issues and further researches should to be carried out in other social media platforms to find out if the same results can be obtained.

### 5.4 Areas for Further Research

Existing literature indicates that as a future avenue of research, there is need to undertake similar research in other social media platforms in Kenya and other countries in order to establish whether the explored emotion detecting platforms herein can be generalized to affect emotion detection in other social media platforms.

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