FACEBOOK USER REACTIONS AND EMOTION: AN ANALYSIS OF THEIR RELATIONSHIPS AMONG THE ONLINE DIABETES COMMUNITY

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ABSTRACT

With the advent of Web 2.0 technologies such as social media, online text sources provide large scale data repositories out of which valuable knowledge about human emotions can be derived. This paper aims to (i) detect and classify emotions of the Facebook diabetes community, (ii) examine the relationship of emotion and Facebook reactions, and (iii) identify user reaction predictors for each of the emotion. A total of 15K posts were randomly selected from several official Facebook diabetes support groups. Pre-processing was administered, resulting in 2475 Facebook posts for further analysis in this study. Emotion detection was first administered using Indico API, with results revealing anger, sadness and fear to be the top most emotions experienced, whilst love and wow emerged as the highest-ranking reactions. Precision and recall indicate the performance of the emotion detection mechanism ranged between 65 – 82% for all the emotions, compared to the human annotation. The average F-score recorded was 78%. Both love and wow were found to significantly predict joy and fear, whereas angry was found to predict anger. The findings indicate that human emotions can be effectively detected based on users' textual communication, and significant relationships exists between several reactions and emotions.

Keywords*: *Emotion analysis, Facebook, Reactions, Diabetes, Social media

1.0 INTRODUCTION

The ability to accurately classify the sentiment of textual communication such as Facebook posts is essential to natural language understanding. Users freely share their opinions, suggestions and experience on social media platforms, and thus generating a lot of studies on sentiment and emotion analysis with applications in social sciences, business, and politics, among others [1-5]. Nevertheless, research on the use of social media for health-related purposes is limited. People suffering from chronic illnesses such as cancer [6, 7], mental illness [8, 9] and diabetes [10, 11] turn to online health communities to seek information, share personal experiences regarding diseases, medical treatments, communicating with other patients, exchange information pertaining clinical, medications and side effects, as well as a life and emotional support [10, 12, 13].

Diabetes distress is highly associated with self-care and glycaemic control [17]. However, this is not the only cause, with other causes being associated with treatment, diet management, complications, emotion imbalance, personal relationships and relationship with healthcare professionals [18]. Being diagnosed with diabetes is challenging as diabetes patients need to overcome the fact that this is a life-long disease and they will need to adapt to many changes. They are also at risk of other diabetes complications like retinopathy, neuropathy, nephropathy and cardiovascular disease, among others [14-16].

With the emergence of Web 2.0 tools such as Facebook, social media has become a platform for many to share their opinions, suggestions and experiences, and thus generating a lot of interests on sentiment and emotion analysis [1-3]. Facebook for example, has become a popular platform for the diabetes communities (i.e. patients and caregivers) to connect, share knowledge and provide peer support to each other. One such online health community is the Type

1 Diabetes Support & Information[1] group, which has over 87K followers comprising of patients, caregivers and medical practitioners, and provides a convenient platform for patients and caregivers to support each other. According to scholars in [10], who examined 690 Facebook diabetes comments, almost 29% of them featured an effort by the poster to provide emotional support to other members.

The large number of online followers in such groups is a testimony on the severity of the disease. Depression, anxiety and distress have been commonly reported among diabetics [18-21]. Information shared by the online community can be value-laden and charged with emotions, influencing attitudes, emotions, beliefs, and behaviours of other users, hence affecting the online and offline world in discernible ways [45]. Emotion is any conscious experience intertwined with personality, mood, temperament and motivation. It plays an important role influencing overall human behaviour where reasoning, decision making, and interactions are affected [24]. Emotion mining or detection is concerned with detecting emotion within written text as joy, sadness, anger, fear, disgust etc. [24, 25]. To-date, efforts in emotion analysis on text sources have mostly focused on detecting emotions of individuals based on the primary emotions (e.g. joy, anger, sadness etc.), ignoring the users' reactions that can be captured automatically on social media. This work is primarily motivated to further examine human emotions by exploiting and investigating the impact of Facebook users' online behaviour, particularly their reactions, and aims to further address this gap by focusing on Facebook diabetes support groups.

The remaining of the paper is structured as follows: Section 2 elaborates on the emotion analysis, followed by Facebook reactions in Section 3. The research methodology adopted is presented in Section 4, and the main results are discussed in Section 5. Finally, Section 6 concludes the paper with limitations and suggestions for future studies.

2.0 EMOTION ANALYSIS

There exist four distinct emotion analysis tasks. First, to detect and identify emotion that is found within a text, often like sentiment detection (i.e. positive, neutral or negative). For example, "*I can't believe my good fortune this morning*" shows positive detection for the emotion. Second is to detect the polarity or intensity of the emotion, for example, "*The sugar-free pudding is very distasteful*" shows disgust but due to the use of the word very, the emotion detected within this sentence is of a higher polarity. Third, emotion classification takes place based on specific emotion categories (e.g. joy, fear, surprised etc.). Therefore, an example sentence of "*The outcome of my blood test is really upsetting me!*" would result in an emotion classification of anger. The final task is to determine the motive or purpose of the emotion. For instance, the motive for "*One of my favourite recipes, so glad to be able to contribute",* can be information sharing [26-28].

Emotion analysis from a given text would be fairly easy if words representing the said emotion were explicitly mentioned. However, in most cases, the emotion expressed is done in a more subtle form and a sentence may carry more than one form of emotion within it. Over the years, a considerable amount of effort is being made in order to produce emotion analysis systems that would be able to correctly identify and classify human emotions from text. Lexicon-approach and machine-learning are two main emotion analysis techniques. Lexicon-approach involves the use of dictionaries that have mapped words to specific emotions (e.g. SentiWordNet) to detect anger, fear, joy and sadness using different textual sources. An example would be the work of [29] who compared various lexicons to detect four primary emotions (i.e. anger, fear, joy, and sadness) using textual sources ranging from fairy tales to news headlines. On the other hand, the machine-learning approach classifies text using syntactic and/or linguistic features and is highly dependent on the availability of labelled or annotated datasets [25, 29-35]. Popular machine-learning algorithms used in emotion analysis are Support Vector Machines [32] and logistic regressions [33].

Alternatively, there are many established and freely available application programming interfaces (APIs) that support text, emotion and image analysis, often provided by giant corporations such as IBM and Google, among others. One such example is the Indico API[2], which is an advanced machine-learning and a freely available application programming interfaces (APIs) that supports text analytics, sentiment analysis, image analysis and emotion recognition. The present study aims to classify users' unstructured online communication into their respective emotions using Indico API.

[1] https://www.facebook.com/Type1DiabetesFacts/
[2] https://indico.io/docs/emotion

3.0 FACEBOOK REACTIONS

Facebook allows its users to post updates, to express their sentiments and emotions by liking, commenting or sharing a post. Unlike Twitter, Facebook has no word limits, hence allowing its users to express their opinions and feelings using textual comments. However, posts were found to receive more likes or shares compared to longer comments [1]. Evidences exist showing how the incorporation of such features facilitated discussion of news, with a general consensus that a higher number of likes and comments indicates users are in agreement with the content [1-2], or an increase in the number of share demonstrates a higher importance of an item to be known by all, hence increasing its visibility and influence [29]. In 2016, Facebook introduced the reaction features as an extension of its like button and are considered a graphical expression of one's emotion [36] to posted contents. Table 1 provides the description and the general sentiment associated with each of these features [42].

Table 1: Facebook Reactions and their Descriptions

Reaction	Description	Sentiment
Like	Users showing pleasure towards the post	Positive
Love	Facebook user completely agrees, in addition to sympathy towards the post	Positive
Haha	User showing sarcasm, liking, laughter, but the feeling is neutral	Neutral
Wow	User shows surprise, however, unclear whether the feeling is positive or negative	Undefined
Sad	User is disappointed by the post	Negative
Angry	User is completely at odds with the post	Negative

Emotion detection is performed primarily on the main posts in Facebook, where additional features such as 'likes', 'reactions' and 'comments' are not widely used as they are considered as noise [46]. Majority of the studies on Facebook reactions have focused on emotion detection, with very few further investigating the impact of these reactions on specific emotions. For example, [43] performed content analysis, and found reactions help marketers understand how consumers emotionally connect with the content displayed. Authors in [47] on the other hand, studied the form of reactions posted on Facebook after the Berlin, London and Stockholm terrorist attacks, with results showing the page administrators disseminating news and information for crisis situation were able to use the number of reactions to predict the form of information that should be uploaded. Similarly, the German government, with data comprising from 25 cities, used Facebook as a channel to communicate with their citizens and saw how the citizens responded to their posts, using their reactions to evaluate the success of the communication [52]. Researchers in [53] used Linguistic Inquiry and Word Count (LIWC) text analysis program to investigate the pro-vaccination and anti-vaccination comments and reactions to overcome the outbreak of diseases. Finally, [36] investigated the use of reactions to indicate sentiment and emotion using Naïve Bayes and lexicons, with positive results showing reactions and emojis can be used to detect sentiment and emotion.

In this paper, we propose to examine the impact and relationships between Facebook reactions and human emotions, particularly the online diabetes community. The study contributes in the following manner:

- Detects and classifies emotions among the online diabetes community to investigate the pattern of emotions expressed the most by this community.
- Examines the relationship of emotion and Facebook reactions.
- Identifies the reactions that significantly predict each of the emotions classified (i.e. predictors for each emotion).

4.0 METHODOLOGY

This study is part of a much larger study looking into the communication patterns of the online diabetes community. However, this paper only focuses on the emotion analysis, and the relationships between users Facebook reactions and emotions. This section presents the processes required for the emotion analysis, emphasizing on the diabetes corpus preparation, emotion classification, and the tools used for these purposes. Fig. 1 depicts the pipeline involved, beginning from data collection to identification of the predictors.

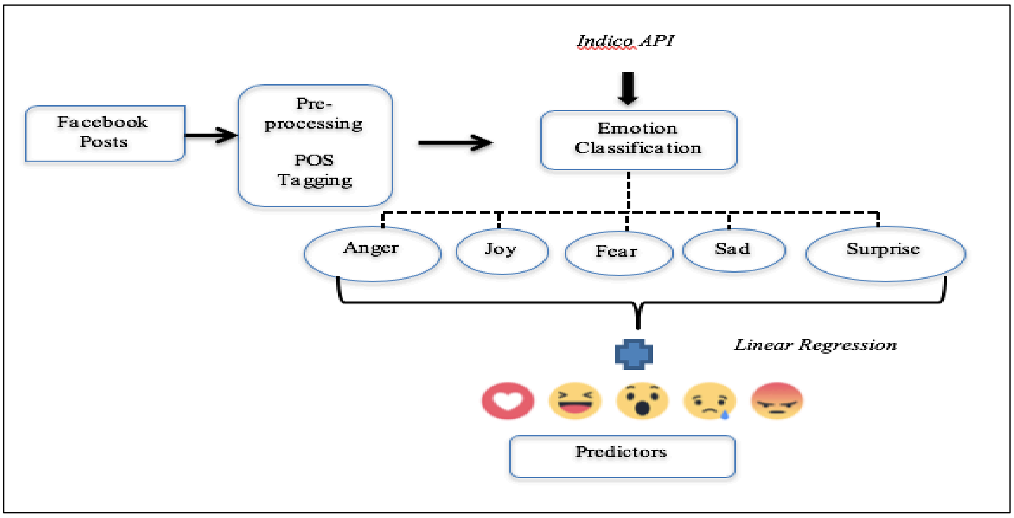


Fig. 1: Emotion Mining Pipeline

A total of 193K Facebook posts were crawled encompassing Type 1, 2 and 3 diabetes covering communications from July 2017 – November 2017, from six official diabetes groups (identities of the sites are withheld for confidentiality purpose). Apart from textual posts, meta-data such as likes, shares, comments and reactions were also fetched excluding replies to the posts. All user IDs were kept anonymous. The data were filtered using several criteria, as part of the pre-processing. These include the removal of URLs, emoticons (i.e. pictorial representation of facial expressions), misspelled words, non-English posts and posts that were too short (i.e. fewer than three words), among others, resulting in 82 120 posts. The posts were then screened whereby those without any reactions were excluded, resulting in 43 022 posts. Of these 43 022 posts, 15K were randomly selected for Part of Speech (POS) tagging, lemmatization and tokenization using the Standard Core NLP parser. Fig. 2 provides an illustration as to what takes place during these processes for a sample sentence "*Have faith. This'll all soon be over*".

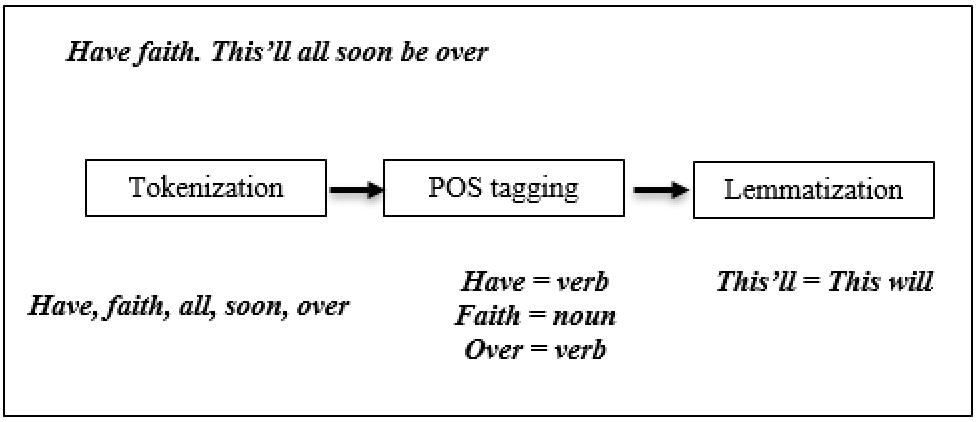


Fig. 2: Tokenization, POS tagging and Lemmatization

Indico API works by detecting emotions and returning a set of five scores (i.e. anger, fear, joy, sadness, surprise) for a post, with the highest score indicating the strongest emotion. For instance, for the sample sentence below, the API produces: anger (0.092), joy (0.021), **fear (0.251),** sad (0.101) and surprise (0.020). Based on the highest score, the final emotion detected would be **fear.**

It doesn't matter what I eat my sugars are still out of control and I'm still petrified of insulin causing fat

In classification studies, an annotated dataset is often required for the purpose of evaluating the accuracy of the classification. This manual annotation is usually a costly-process in terms of its resources, therefore, we randomly selected 8K posts to be annotated by seven experts comprising of medical practitioners and linguists. The experts were required to read each posts and classify it based on three main classifications (i.e. each classification had approximately 2500 posts), namely, sentiment (i.e. positive versus negative), purpose/motive and emotion (i.e. sadness, joy, anger, surprised and fear). The total valid posts annotated for emotion were 2475 (i.e. 40%), with an established inter-coder reliability of 0.85 (i.e. Krippendorff's alpha).

The standard evaluation metrics, namely, precision[3] (number of correct classifications that matches the human annotated count), recall[4] (ability of the classifier to correctly classify the emotion against the total dataset) and F1-score[5] (uses precision and recall to compute its score and is often used when the class distribution is uneven) were used to assess the accuracy of the emotion analysis. All these metrics work by comparing an extracted value (i.e. emotion) produced by the emotion classifier to the human annotated result [37]. The scores for all three metrics range from 0 (worst) to 1 (best), therefore, a higher score indicates a better classification.

SPSS 25 was used to administer both the descriptive and inferential tests with regards to Facebook reactions and user emotions. In terms of the emotion classifications and frequency of reactions, frequency and percentage were used to describe the diabetes data. Linear regressions were used to identify the reactions (i.e. predictors) for each of the emotions.

5.0 RESULTS AND DISCUSSION

5.1 Emotion analysis

The study first detected the emotions among the Facebook diabetes community. Table 2 depicts the effectiveness of the emotion analysis performed using Indico API. In general, it can be observed that the scores for all the metrics are between 65% - 82%, indicating good classification accuracies compared with the manual (i.e. human) annotation. In fact, the average scores for the emotions are more than 75%, regardless of the metrics used. This is in line with several emotion analysis studies, in which the average effectiveness was reported to be within the range of 61.3% to 85% [48-50]. It is to note that however, effectiveness cannot be directly compared as any form of classification depends severely on domains and topics of study [48]. For instance, [48] and [49] worked on Chinese languages, using different emotion classifications (i.e. [48] used Ekman's [51] six emotions whereas [49] used only happiness and popularity). On the other hand, [50] compared machine learning and lexicon approaches on English tweets, with an overall accuracy of 80.68% for machine learning and 75.2% for the lexicon approach.

Table 2: Effectiveness of the Emotion Classification

Emotion	Precision	Recall	F1-score
Anger	0.820	0.796	0.816
Joy	0.801	0.812	0.816
Sadness	0.810	0.791	0.801
Fear	0.796	0.787	0.749
Surprise	0.695	0.606	0.716
Average	**0.784**	**0.751**	**0.780**

5.2 Facebook reactions and emotions

Fig. 3depicts the overall reactions fetched for the 2,475 posts. It can be observed that more positive reactions had been used by the online diabetes community, with love ranking first, followed by wow, sad, angry and finally haha. This shows that people are more likely to click on the positive reaction (i.e. love) compared to the negative reaction (i.e. sad and angry), concurring with literature findings that in groups that cater for health-related issues, people tend to be more supportive of one another [38, 39], hence the use of positive reaction outnumbers the negative.

[3] $Precision = \frac{\sum positive\ data\ that\ match\ human\ classified\ count}{total\ positive\ data\ produced\ by\ tool}$

[4] $Positive\ Recall = \frac{total\ positive\ data\ that\ match\ human\ results}{total\ positive\ human\ classified\ data}$

[5] $F - measure = \frac{2\ x\ precision\ x\ recall}{precision + recall}$

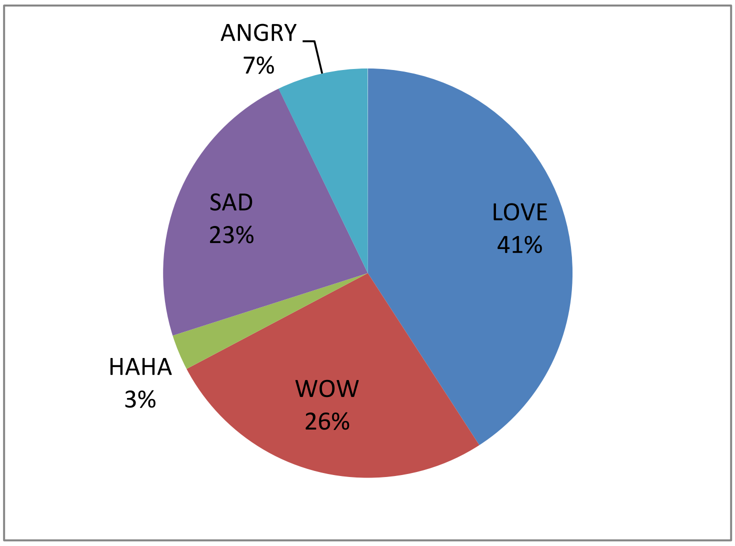
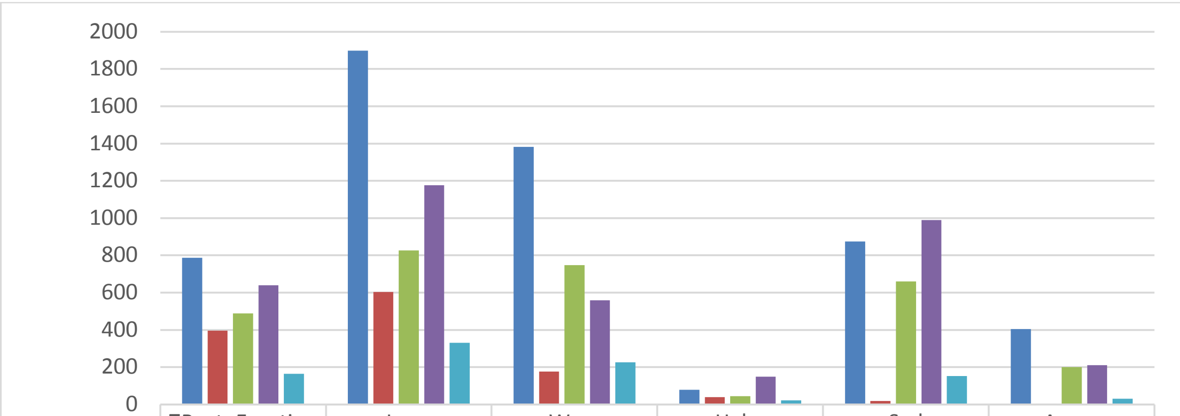


Fig. 3: Overall Facebook reactions

Fig. 4 illustrates the breakdown of each of the five emotions with relevance to the reactions. The first column (i.e. ∑ Post_Emotion) represents the number of posts for each of the five emotions.



	∑Post_Emotion	Love	Wow	Haha	Sad	Angry
Anger	787	1899	1382	79	874	404
Joy	395	603	176	39	19	5
Fear	489	827	747	44	660	200
Sadness	640	1176	558	149	990	210
Surprise	164	331	226	22	152	30

Fig. 4: Emotion Classification and their Respective Reactions

In terms of emotions, anger ranked the highest (32%), followed by sadness (26%) and fear (20%), probably due to the nature of the chronic disease dataset used. The dataset (i.e. topic) used probably also explains the reason behind the low usage of haha. Nevertheless, the emergence of all three negative emotions at the top implies the grave nature of the disease, and the pain endured by the patients and caregivers. Compared to all the reactions, love emerged to be the top-most used Facebook reaction among the diabetes community, across all the emotions. It can then be inferred that the community shares the joy (e.g. when one's glucose reading improves) and the pain (e.g. when one struggles to maintain their diet) by showering love and rendering support. For instance, love ranked as the highest reaction for anger, indicating support and love provided by community members to those expressing anger. A similar pattern was observed for fear and sadness, where the majority of the people reacted by showing love to those suffering. The sad reaction shown towards sadness indicates that members do sympathize with the patient's situation and this shows a caring and concerned community. Community members felt angry as well given that one has to endure such a suffering or situation. In fact, as shown in Figure 2, negative reactions were highest for all three negative emotions. For instance, Anger garnered 404 angry reactions compared to joy, with only 5 angry reactions. The same pattern can be observed for sadness as well, whereby 990 sad reactions were noted compared to only 19 for joy. This finding is further supported by the regression results in Table 3.

Table 3 shows the significant predictors of the reactions for each of the emotions. It can be observed that only the angry reaction significantly predicts anger among the diabetes community. Anger is one of the most common negative emotions that can be expressed in response to other's action. When an angry comment is posted or shared, the community deemed to react accordingly to show that they too agree, hence an angry reaction is reflected.

Table 3: Linear Regression for Facebook Reactions and Emotions

Emotion	Reactions	R^2	Beta	F (*p-value*)	t	*p*-value
Anger		0.17	0.16	3.074 (*0.001*)		
	Angry				1.924	0.044
Joy		0.31		7.445 (*0.000*)		
	Love		0.15		2.985	0.003
	Wow		-0.10		-2.815	0.005
Fear		0.06		2.133 (*0.024*)		
	Love		-0.10		-3.248	0.001
	Wow		0.09		3.076	0.002
Sadness		0.26		4.163 (*0.000*)		
	Wow		-0.10		-3.514	0.000
	Sad		0.11		3.754	0.000

Note: Only significant results are shown;

Anger = 0.267 + 0.16(Angry);
Joy = 0.168 + 0.15(love) – 0.1(Wow);
Fear = 0.213 – 0.10(Love) + 0.09(Wow);
Sadness = 0.253 - 0.10(Wow) + 0.11(Sad)

Both wow and love were found to predict two conflicting emotions, that is, joy and fear. As per Table 1, wow is classified as "undefined", implying the difficulty to associate this reaction to a specific sentiment (i.e. positive or negative). Therefore, this probably explains the emergence of wow as a significant predictor for both the positive (i.e. joy) and negative (i.e. fear) emotions. Fear can be associated with patients feeling nervous, scared or being in an alarming situation. Members of community may express their surprise in patients fear as a sign to calm them down as well as giving them the strength to overcome their emotion. This is contrary to love, where the reaction can be associated with members of the diabetes community to share happiness when a "happy" post is posted, while showering love when someone shares their fear related to the disease [38-39].

Finally, wow and sad were found to predict sadness. Sad reaction is used as a supportive reaction [40] to show that they do understand the patient's emotions. As an ambiguous reaction [41], members reacted with a wow to sadness to acknowledge the emotion conveyed. Patients can look at it as an optimistic look for them to move on quickly to the future from their otherwise difficult or distressing situation. The wow reaction by the members could also indicate a significant or powerful or expressive way that reflected the patient's emotion at the time of the post. Nonetheless members show their support and care for a sadness emotion with a sad or wow reaction. Finally, no significant predictors were noted for surprise, which is also the lowest ranking emotion compared to the rest.

6.0 CONCLUSION, LIMITATION AND FUTURE WORK

This study analysed the emotions among the online diabetes community, and further investigated the relationships between user behaviours (i.e. reactions) with specific emotions. An analysis of 2475 Facebook posts revealed anger, fear and sadness to be the common emotions among this community, a somewhat expected result considering the nature of topic investigated. As for user reactions, love emerged as the highest ranking reaction to these posts, regardless of the emotions, though more occurrences were noted for anger and sadness. This suggests a tight support system among the members of the Facebook diabetes community. Our findings are echoed in similar studies that have reported online health communities to support each other in times of need with their positive reactions. These Facebook posts covers a wide range of topics from dietary, medication, recipes, financial burden, relationship, tips and recommendations, experiences and not forgetting their emotions building and revolving these topics. Members of the community do play a part in providing their support and concern which probably resulted in love being the most used positive reaction. Looking at the negative reactions (i.e. sad and angry), the study found linear relationships between the said reactions and negative emotions. In fact, regressions provided further support when the reactions emerged as significant predictors for the emotions. Our findings are echoed in similar studies that have reported online health communities to support each other in times of need [10]. Additionally, findings show significant connections between certain user behaviours (i.e. reactions) with the emotions they portray online.

The study though, has several limitations. First, the size of the dataset used. Though the data were part of a much larger study, the number of posts with reactions used for annotation was only 2475. This is considered acceptable compared to other studies [10], however, a larger dataset may be able to produce a better accuracy. Human annotation is an expensive task, therefore, future studies could investigate other alternatives, such as crowdsourcing. Second, the study used Indico API for emotion detection, with only five emotions being detected. Future studies can extend the scope by using other wheels of emotions such as Ekman's six basic emotions (i.e. Anger, Disgust, Fear, Happiness, Sadness, Surprise) [51] or Plutchik's eight emotions (joy, trust, fear, surprise, sadness, anticipation, anger, and disgust [26]).

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