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Recognizing Human Needs During Critical Events Using Machine Learning Powered Psychology-Based Framework

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ABSTRACT We propose a psychological need detection framework which automatically identifies people needs and measures their satisfaction level. The framework employs three need models, which are developed using psychological, linguistic, and Twitter-specific features. We evaluate the performance of the proposed models on psychological need data sets which are annotated by psychologists. The models obtained encouraging results: 78.71% in recognizing need content, 81.96% in identifying need type, and 93.56% in measuring need satisfaction level. We use the proposed framework to recognize individual needs and measure their satisfaction level in response to the Florida shooting event, which occurred on February 14, 2018, and the related March for Our Lives event which followed on March 24, 2018. Timeline-based visual and textual representations are generated to explain the motivation behind public reaction and behavior.

INDEX TERMS Human needs, machine learning, affect-aware city, critical event, need satisfaction, social media analytics.

I. INTRODUCTION

Social media platforms have evolved into a powerful medium in the distribution of breaking news and in connecting people during real-world events such as sports, politics and crises. Through social media, people circulate geographic and time based updates in real time through eyewitness texts, images and videos, all of which are publicized prior, during and following significant events. Furthermore, these real time updates evoke individual opinion, thought, insights, evaluation and emotion in relation to such events. Unlike traditional media, which is limited through reporting single-perspective news headlines combined with multimedia based solely on fact, social media is more apt to shed light on public reaction or opinion towards political, religious or terrorism events, making it a powerful tool in deciphering the temperament of a population.

As social media platforms continue to evolve, they have become the most valuable, reliable and easily accessible data source which reflects different human affective states. Inspired by the importance of recognizing human affective states from different modalities like physiology, face and voice [1], [2], a new form of sensing that employs the idea of citizens themselves as ‘‘soft sensors’’ has emerged and attracted considerable interest lately. As stated by the Affect-Aware City vision [3], an individual's diverse affective states, including emotions, mood, and personality traits, can be utilized to complement traditional physical sensors in order to achieve real time awareness and create a big picture of the live state of the city. Recognizing and analyzing the affective states of individuals within a society is an essential tool in public policy development. The interpretation of the analyzed affective states can guide stakeholders and authorities in improving situational awareness and help to actualize effective planning for the future.

Researchers have started mining this massive resource of affect data in many large-scale temporal and geographical predictive and analytic applications. For instance, analyzing public opinions regarding a political candidate [4], opinions towards newly released brands and products [5], and monitoring local and global happenings [6]. Moreover, social media content has been used to capture individual real time responses during disasters [7] and environmental emergencies [8]. Despite the recent focus on analyzing distinctive human behavior and affective states before, during and after critical events, the exploration around the "why" behind these feelings, actions and behaviors, to date, has received very little attention. One factor that could explain the motivation behind various behaviors and actions are the basic human needs.

Human Needs Theories (HNTs) provide root explanations of human feelings, and, in turn, what motivates an individual's actions and behavior in various situations [9]. Furthermore, they provide valuable insight into the primary causes of conflict and the root of violence by claiming that unmet needs or dissatisfied needs lead to violence and conflict. For example, a definition of *need* from a political science perspective, says: "Human needs are a powerful source of explanation of human behavior and social interaction. All individuals have needs that they strive to satisfy, either by using the system, acting on the fringes or acting as a reformist or revolutionary. Given this condition, social systems must be responsive to individual needs, or be subject to instability and forced change possibly through violence or conflict". Accordingly, our goal is to shed light on the vast benefits of automatically recognizing human needs and measuring satisfaction levels using social media content in order to avoid violence and conflict.

In this paper, we propose an automatic human need detection framework which employs three models in determining individual needs and measuring satisfaction levels. This proposed framework utilizes a psychological multi-layer framework that is built based on theoretical knowledge. In developing and validating the proposed need models, we used a psychological need data set that is manually annotated by psychologists. For each layer, based on the concept being analyzed, we investigate the utility of several features, including linguistic, psychological and twitter-based features. We apply a feature selection method in order to solve sparse and high dimensionality feature space problems. As a case study, we analyze public needs in response to a Florida shooting event from February 14, 2018 and the related March for Our Lives event which scheduled on March 24, 2018.

The rest of this article is structured as follows. In Section II, we provide a brief overview over the literature concerning the analysis of psychological needs. In Section III, we introduce the proposed human need detection framework, and we give a detailed description of all the steps that we performed to develop the need models. In Section IV, we describe the experiments conducted to evaluate our models and present the obtained results. In Section V, we use our developed models to recognize individuals' needs, and measure their satisfaction level in response to the Florida shooting event and March for Our Lives event. Our conclusion is drawn in Section VI with a summary of the main findings, suggestions for future directions, and possible practical applications.

II. RELATED WORK

Human needs play an important role in providing root explanations of individual feelings and, in motivating a person's actions and behavior. Individual needs are typically assessed using approaches from psychological science, which include personal interviews, social observation, self-report and surveys (i.e. psychometrics) [10]. Due to many limitations, these traditional approaches are now considered inadequate for large-scale need identification and analysis. First, assessment methods such as face-to-face interviews and social observations are usually done more than once in a life time, and it is therefore difficult to get comparable results when collecting information in an interactive way within a large group (i.e. community). Second, psychometric surveys are very time consuming, and only reflect a small percentage of the entire population within a city or community. Third, most of human need psychometrics (surveys) are designed to measure individual need satisfaction with respect to one specific life aspect (i.e. relationships, work, education, etc.). This design specification makes the real time analysis of millions of individual satisfaction levels within different life domains even more challenging.

To overcome these limitations, we aim to develop an analytical and computational framework that utilize the dynamic nature of social media data and metadata to recognize individual psychological needs and assess their satisfaction levels in large scale venues such as cities and communities.

People frequently use social media platforms such as Twitter to broadcast their opinions, insights, evaluation and perspectives about their surrounding environment in real-time. The dynamic nature of these platforms generates a large repository of User-Generated Content (UGC) that is publicly available and openly shared. Therefore, it is now more feasible to collect, analyze and understand social media content in order to better interpret and make sense of the behavior of millions of individuals in response to critical events than it was ever possible through traditional methods. Fowler [11] and Barnaghi *et al.* [12] use Twitter to break the news about a given crisis and analyze public sentiment (positive and negative) towards the events. Jones *et al.* [13] use Twitter data to study the impact of violence on communities by analyzing negative emotion words. Buntain *et al.* [14] use Twitter as critical information sources and trace Twitter activities during terrorist attacks. In addition, Wang *et al.* [15] predict crime from Twitter content through semantic analysis.

Several attempts have been made to explore the use of social media content to infer people need. They differ in their perspective, objective and theoretical background. For instance, an IBM Research group [16] explored the identification of individual fundamental needs based on consumer behavior and product categories which were mentioned on social media. Due to the lack of standard instruments that identify the needs that influence purchase behavior; they developed their own psychometric scale through a crowd-sourced study. The development of this psychometric is based on Ford's needs model, which was inspired by the Maslow hierarchy of fundamental needs. The model has 12 need categories which correlate and explain consumer behavior, namely: structure, practicality, challenge, self-expression, excitement, curiosity, liberty, ideal, harmony, love, closeness and stability. In the psychometric test, participants were asked to list the names of three products they would like to buy and write about their need that matches the model during that moment. The authors used the list of product categories obtained from the responses to collect the data. For each product category, they used Amazon to generalize the product names that belong to this category, and then used these names as search queries to retrieve six million tweets, construct the data set, and built their need model. Although they were the first to attempt to detect user need from social media, their approach has many limitations in recognizing needs from a psychological well-being perspective. For example, the objective of their work is geared towards enhancing the quality of direct marketing and influencing purchasing behavior. Thus, their proposed model is limited to identifying the individual's needs based solely on consumer behavior. Moreover, the underlying need theory that was used to build their model was restrained by its cultural and hierarchical limitations. Most importantly, the method relies on the product categories to identify the underlying needs. The product categories, also known as satisfiers, refer to the ways people satisfy their needs. Based on the Manfred Max-Neef need theory, needs are fairly stable; whereas, satisfiers are variable and dependent on gender, age and culture, and can even change and evolve for the same person over time. Therefore, we cannot rely on satisfiers to predict the need states. Lastly, the tweets used to construct their data set and to train the need model only expresses closeness and ideal needs. Table 1 shows examples of tweets expressing closeness and ideal needs.

TABLE 1. Tweet examples for closeness and ideal needs from the IBM need data set.

Need Type	Type of product	Tweets
Closeness	Home Decorations	*"**I just bought** skittle candles"*
Ideal	Organic Food	*"**I bought** organic milk today. Just thought you would be proud.."*

The classification of sentences in personal stories (web-blogs) based on seven human needs has been attempted by Ding *et al.* [17]. Their work has many shortcomings in both the theoretical background and the classification method. There is no concrete guideline in defining the needs categories, their theoretical base is not connected to a specific need theory, nor was an expert consulted prior to proposing their taxonomy of needs and performing their annotation process. Also, they associate the concepts of basic human needs with desires, wishes and goals, which are considered separate and unique entities in many psychological need theories. Moreover, the number of instances in their dataset (approximately 559) is too small for a classification task involving more than seven classes. This may explain the resulting poor performance (54.8 average F1).

Ghazi *et al.* [18] address the problem of recognizing the causes of emotions from a linguistic perspective. They explore the detection of the causality in emotional expression and phrases. They build a first English data set consisting of 820 formal sentences annotated with Ekman's six emotions aside from shame. A Conditional Random Field (CRF) model was developed to detect emotion stimuli using syntactic, semantic and corpus-based features.

Although their approach is interesting, it is limited to the recognition of different nominal and verbal linguistic clauses (i.e. towards, at) as a textual signal of the emotion stimuli without any further analysis or interpretation of the underlying triggers for emotions from a psychological need perspective.

In this paper, we aim to automate the detection of psychological needs by proposing a need detection framework that employs three need models. The models are developed based on a theoretical multi-layer framework which recognizes need content, identifies the need type and measures the need satisfaction level. The proposed framework aims to overcome the challenges present in the traditional psychological measurement methods and transcend the limitations of existing works.

III. METHODOLOGY

The human-need detection framework is developed to automatically detect the need expressed in social media textual content and analyze the satisfaction level. It consists of two main phases: the offline phase for training and testing which is demonstrated by the flow diagram in Fig. 1 and the online human need detection and analysis phase that is explained by the flow diagram in Fig. 6.

The offline phase illustrates the learning process to develop the need models, namely the Recognizing Need Content (RNC) model, the Identifying Need Type (INT) model and the Measuring Need Satisfaction (MNS) model. It explains the dataset used throughout the experiments, the preprocessing step, the feature sets explored, the sampling techniques used to balance the classes' distribution, and the dimensionality reduction step, which are explained below.

A. BASIC PSYCHOLOGICAL NEED DATA SET

We used the psychological human need data set which created using a theoretical-based multi-layer framework [19]. The data set consists of 18,847 tweets that are labeled manually by three psychologists. Out of the 18,847 tweets, 6334 tweets reflect individuals' emotions and convey their psychological basic needs. Each tweet has three labels corresponding to the three need concepts as defined in the theoretical framework layers. Fig. 2 shows a diagram of the multi-layer theoretical-based framework. The layers in the framework are constructed based on several psychological need theories [20], [21].

The first layer of the framework captures the needs signs and signals. Since basic needs are invisible and implicitly expressed, they can be observed and recognized through emotions and feelings as indicated by most psychological need theories [20]. Therefore, in the first layer, we recognize and

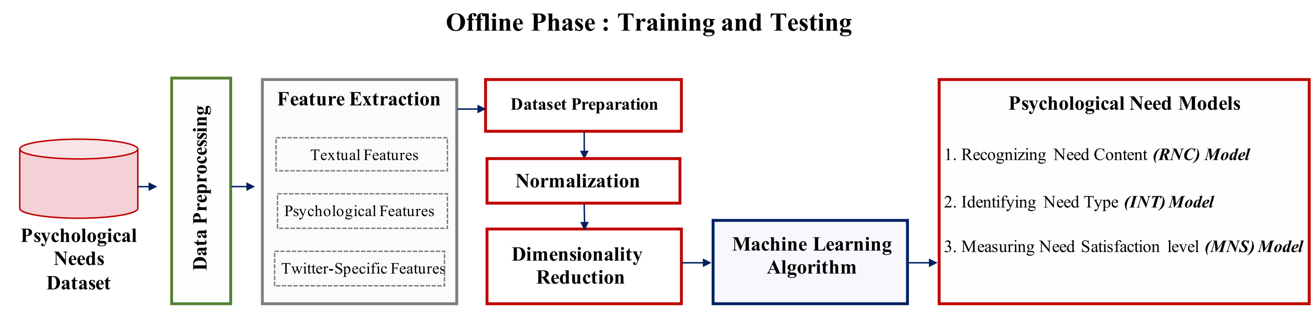


FIGURE 1. An overall flow diagram describing the offline phase for the proposed human need detection framework.

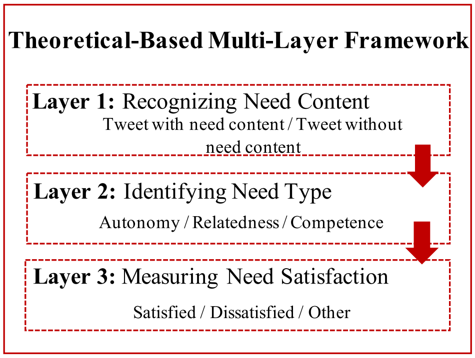


FIGURE 2. The theoretical-based multi-layer framework that used to construct the psychological need dataset [19].

verify the emotional content that truly reflects the individual's underlying need state.

The second layer identifies the type of needs that are present. To ensure the validity of our framework, we consider the basic psychological needs that are innate, fundamental, and universal, as postulated by the Basic Needs Theory (BNT) [22], [23], a sub-need theory within the Self-Determination Theory (SDT) framework [9]. BNT proposes three needs: autonomy, competence, and relatedness, for all individuals, regardless of their gender, age, culture, ethnicity, religion, or socioeconomic status. These three needs allow individuals to feel satisfied, and in turn, promote well-being and prevent conflict and violence [9], [24]. Measuring the satisfaction level of the three needs can predict the daily well-being and provide valuable insight into the primary causes of conflict and the root of violence. Based on SDT, unmet needs lead to violence and conflict. The need for autonomy is described as the need for individuals to self-endorse their behaviors or the willingness to engage in activities through their own personal choice without any external pressure. The need for competence refers to the need of individuals to experience opportunities in which they can effectively interact with their social environment and to successfully express their capabilities and talents. Finally, the need for relatedness is described as the need to feel connected and involved with others, and to experience reciprocal caring with friends and family or even with larger groups or communities (e.g. religious or political).

After identifying the need type in the second layer, the level of need satisfaction is measured in the third layer. The polarity and the intensity of the emotions experienced help to determine the state of fulfillment of needs.

B. DATA PRE-PROCESSING

There is no universal or standard method of data pre-processing as it is dependent on the goal of the classification task and the concepts that need to be analyzed. In this work, we are focusing on textual messages from Twitter as a first attempt to classify human needs. Accordingly, all other Twitter elements including URLs, videos, images, Twitter interactions such as mentions and replies were filtered out in the offline phase. We kept hashtags, since they summarize and emphasize the meaning of the tweets, and emojis which are heavily used in Twitter to present feelings. We also kept punctuation, decoration symbols and numbers such as "10.0", "1" and "1st" since they are expressive and can be useful to understand the scope and the intention of the writer. All the tweets then passed through the tokenization process, using the Twitter-specific Tokenizer from the TweetNLP Ark tool.[1] The hashtag "#" and the attached words, i.e., #Love, are considered as one token in order to preserve their meaning. We convert all words in the document into lowercase. Then, we pass all the words through the SnowBall [2] stemming algorithms which stem the words by applying different transformation rules to keep the root forms of the word. Most of the previous subjective analysis works removed stop words such as pronouns, conjunctions, and/or articles [25]. Stop words are considered to be noisy and not informative due to the high-frequency occurrence. However, in our classification, personal pronouns could be informative words within the first layer. They can be good indicators of the inner emotional and psychological needs as pointed out in the NVC Theory [20]. Therefore, we kept all the stop words.

C. FEATURE EXTRACTION

Feature extraction is the process of representing each tweet as a feature vector. Each entry position in a vector corresponds

[1]http://www.cs.cmu.edu/ ark/TweetNLP/
[2]http://www.nltk.org/api/nltk.stem.html

to a feature type extracted from a tweet and represents the weight of that feature. We explore the usage of text-based features, psychological features, and Twitter-specific feature including hashtags and emojis as elaborated below.

1) TEXTUAL FEATURES

- Bag of Words Model (BoW)

We investigate the standard textual feature *Bag-of-Words* (BoW). The BoW model creates a dictionary with a fixed size that has a list of all distinct tokens in the data set regardless of their order, grammar or the semantic dependency between them. Each tweet is represented as a vector of a fixed length, each position in the vector corresponds to a word from the BoW dictionary. To reflect the relevance of each word in the vector, we use the Term Frequency-Inverse Document Frequency (TF-IDF) weighting schema. A minimum frequency of 3 was set for each word to be considered as a feature and included in the dictionary.

N-gram

- Language Model (LM)

An N-gram is a continuous sequence of n words or tokens. LMs can provide comprehensive information by capturing the meaning of multi-word expression. For example, they can capture patterns for need expression such as the representation of the phrase "I feel", or "I need", which the BoW approach ignores. We used the most common size, which are bigrams ($n = 2$) and trigram ($n = 3$) as well as exploring with 2≥gram≥1, 3≥gram≥2 and 3≥gram≥1. In this model also, we kept n-grams that appear at least three times in the entire data set, including punctuation, numbers and emojis. The vector for each tweet is formed by extracting each n-gram and calculating its TF-IDF weight.

2) PSYCHO-LINGUISTIC FEATURES

We explore psycho-linguistic features and evaluate how effective they are in providing insight into the way people express their needs on Twitter.

- Linguistic Inquiry and Word Count (LIWC)

We used the Linguistic Inquiry and Word Count (LIWC) collection of lexicons [26], which were designed and validated based on psychology and cognitive theories. LIWC consists of a set of 92 lexicons with many dimensions, including: linguistic, personal, cognitive and psychological related lexicons which were developed by psychologists. It has been developed with the intention of analyzing the language associated with psychological concern and has been used widely in detecting personality trait, mood and mental health disorders. For example, the psychological lexicon has social process, affective process and cognitive process dimensions. Each dimension has many categories. For example, the cognitive process dimension has insight, causation, discrepancy, tentative, certainty, inhibition, inclusive and exclusive categories. LIWC information is extracted from each tweet by comparing each word in a tweet with predefined categories. When a matching word is extracted, the LIWC model calculates the percentage of total words that match each of the dictionary categories and forms the vector.

- Linguistic Category Model (LCM)

To better understand the social psychological processes, we use a conceptual model proposed by Semin and Fiedler [27] to analyze the usage of language in interpersonal events. LCM is a linguistic classificatory approach that classifies verbs people use during any social events. It consists of three linguistic categories: Descriptive Action Verbs (DAVs), Interpretative Action Verbs (IAV), and State Verbs (SV). First, Descriptive Action Verbs, are highly informative verbs that provide specific and concrete descriptions of actions during a short duration, such as hit, hold, jog. They have physicality features and clearly define the beginning, the end and the nature of the action. They are also neutral in themselves unless combined with semantic valence. This category contains 2801 verbs. Second, Interpretative Action Verbs, are verbs that describe enduring behaviors and events without describing the feature of the action, such as avoid, help, and attend. This category has a clear positive and negative semantic and it contains 4062 terms. In contrast, State Verbs are related to thoughts and affective states. They refer to invisible cognitive states, such as think, understand, or specific emotional states evoked by an action that a person feels and experiences during an event such as love, hate, respect. This category consists of 626 verbs. By using this model in our need detection framework, we can capture not only what is happening to a person, but also, their psychological state during the event, as well as the characteristics of the others involved in the event. Furthermore, we can determine the duration of the event. For the LCM features, we calculate the frequency of all descriptive (DAV), interpretative (IAV) and state (SV) verbs in a given tweet.

- Sentiment Lexicons

To measure the satisfaction level in the third layer of the framework, we rely on the relation between the arising emotion and the underlying need. Based on the Self-Determination Theory and the Non-Violent Communication Theory [20], [22], the emotions expressed signal the state of fulfillment of the needs. Positive and pleasant emotions (e.g., happy, pride, excitement) arise when the need has been met and satisfied, while unmet needs generate negative emotions (e.g., sadness, shame and loneliness). Thus, the polarity of the emotions helps to determine the state of fulfillment of needs. Consequently, we adapt features that are driven by the use of existing general-purpose sentiment lexicons such as Bing Liu's Opinion Lexicon [28] and NRC Hashtag Sentiment [29]. We have modified the NRC Hashtag Sentiment lexicon by excluding a number of elements which we have deemed as useless in our scenario. Examples for removed elements are numbers, mentions, punctuation and other non-functional words. For each tweet, we calculate the frequency of each word in the above-mentioned lexicons to form the vector.

TABLE 2. Psychological need data set statistics before and after applying resampling.

Framework Layers	Class Name	Resampling Technique	% Amount of Resampling	Instances Before Resampling	Instances After Resampling
Layer (1)	Tweets with need content	-	-	6334	6334
	Tweets without need content	Under-sampling	29.50%	12513	8826
Layer (2)	Relatedness	Under-sampling	36.6%	3333	2111
	Autonomy	SMOTE	19.5%	1771	2113
	Competence	SMOTE	72%	1229	2116
Layer (3)	Satisfied need	-	-	3295	3295
	Dissatisfied need	-	-	2566	2566
	Other	SMOTE	591%	348	2653

3) TWITTER SPECIFIC FEATURES

Emojis have become an important form of communication in online social networks [30]. This is especially true for Twitter due to the length limit imposed on individual tweets. Researchers investigate the communicative role of emojis in different areas such as clarifying the ambiguity in online conversation [31], expressing emotions [32] as well as revealing aspects of human behavior [33]. Thus, we explore the use of emojis in four ways: the emoji frequency in a tweet, the sentiment of the emoji, the categories of emojis and the color of the emojis.

- Emoji Frequency

We count the number of emojis used in a tweet and consider it as a feature in all the three layers. We used the twitter emojis listed in Emojipedia [3] and create a list with 1519 emojis.

- Sentiment of Emojis

We utilize the emoji sentiment lexicon created by Novak [34] as a feature in the third layer to leverage the satisfaction level expressed. The lexicon consists of 751 emojis annotated manually by 83 human annotators as positive, negative and neutral.

- Categories of Emojis

Emoji characters are not limited to smiley faces meant to communicate affect, but have evolved to also include emojis that represent concepts, ideas and objects [35]. As an exploratory study, we aim to examine the communication role of the different categories of emojis in order to reveal the underlying psychological need type in the second layer as well as the need satisfaction level in the third layer. We selected the most common categories in Emojipedia that include: foods and drinks, animal and nature, flags, weather, object and tools, smileys and people, symbols, activity and sport, and travel and places.

- The Color of Emojis

We explore the rule of the emoji's colors including: black, cream white, dark brown, moderate brown and pale emojis in indicating need type in the second layer and the need satisfaction level in the third layer.

- Number of Hashtags

We also explore the number of hashtags in tweets. For each tweet, we calculate the frequency of "#words" to form the vector in the first layer.

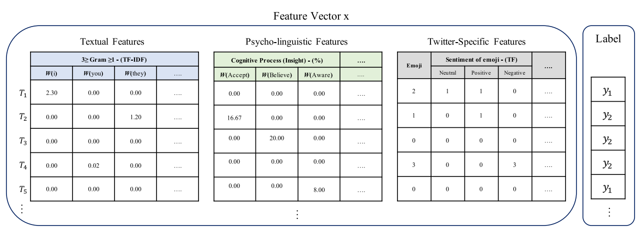


FIGURE 3. Examples of feature vectors x created for the training phase.

Fig. 3 shows examples of feature vectors x created for the training phase. Each row represents a feature vector x_i and its corresponding label y_i. The feature vector examples explain the way the indicators variables are measured and represented for some of the textual feature, Psycho-linguistic features and the Twitter specific features.

D. DATA PREPARATION

Since the data set has been constructed based on subjective psychological real-world observations, we faced a high class imbalance problem. An imbalanced data set can affect the classification task because the training classifier on an imbalanced data set is more likely to be biased towards the majority class and, therefore, misclassify the minority class [36]. A number of solutions have been proposed to solve this problem [37]. Based on the nature and the importance of the classification task in each layer of our framework, we solve the class imbalance problem using one or more of these proper approaches as follows:

[3]https://emojipedia.org

In the first layer, we have imbalanced classes with a ratio of 2:1; for tweets without need content versus tweets with need content. Therefore, we use an under-sampling technique to balance the distribution of classes. We choose to randomly remove 29.5% of the majority class instances in order to avoid losing too many informative instances. Table 2 shows the class distribution before and after using the under-sampling technique.

In the second layer, which represents the core aspect of our framework, the ratio between the three need classes is (2.0:1.0:0.1). We balance the class distribution by using under-sampling and over-sampling techniques simultaneously. For the majority class, relatedness, we used an under-sampling technique to randomly remove 36.6% of the instances. In addition, we increase the number of instances in the minority classes competence and autonomy, by using a powerful over-sampling technique called Synthetic Minority Oversampling Technique (SMOTE) [38]. Rather than over-sampling by replacement which duplicates instances from the minority class in the data space, SMOTE generates synthetic samples based on the feature space. Given an imbalanced data set S, the number of synthetic samples required N and the number of nearest neighbors K (in our case $K = 5$), SMOTE generates synthetic samples for the minority class by performing the following steps:

For each instance x_i in the minority class S_{min}, $x_i \in S_{min}$ in the data set S:

Find its K nearest neighbors $\bar{x}_i$ using the Euclidean distance. Randomly select one of the K nearest neighbors. Then, calculate feature vector differences between the original x_i and its neighbor $\bar{x}_i$. Finally, multiply this difference by a random number $\alpha \in [0, 1]$ and add it to the feature vector:

$$x_{new} = x_i + (\bar{x}_i - x_i) * \alpha$$

In the third layer, since we are more focused on detecting the satisfaction level of the need expressed whether it is satisfied or dissatisfied, we combine the instances of the other two categories (neutral and not clear) in a new class called "Other" Then we use SMOTE to generate 591% more synthetic samples for the lowest class "Other".

E. NORMALIZATION

Because our feature sets are differently expressed and have varying scales, features in greater numeric ranges may dominate those in smaller numeric ranges. To ensure that we capture the accurate information, we use Min-Max scaling, a feature scaling method, after the feature extraction step:

$$x_{sc} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

This scales each attribute to a fixed range. In our case, we choose [0, 1]. As a result, we obtain a feature vector that has similar ranges in each dimension.

F. DIMENSIONALITY REDUCTION

In any raw data set, there are a large number of irrelevant and noisy features that do not provide useful information to the constructed model but lead to a high dimensional feature space that negatively affects performance. Thus, it is important to reduce the dimensionality of the feature space by discarding irrelevant or redundant features. Based on the feature selection guidelines proposed by Guyon and Elisseeff [39], we consider the use of the Gain Ratio (GR) [40], a filter-based technique based on the information-theoretical concept of entropy. It is a modified version of the Information Gain (IG) that measures the reduction in entropy of the class variable after observing a feature. The Information Gain IG is calculated using the following equation:

$$IG(x) = H(D) - \sum_j \frac{|D_j|}{|D|} H(D_j)$$

Where is $H(D)$ is the entropy of the given data set D and $H(D_j)$ is the entropy of the j_{th} subset generated by partitioning D based on feature x. The Entropy for a data set D with class labels Y is defined by

$$H(D) = \sum_{i \in Y} P(i) log P(i)$$

where $P(i)$ is the probability of class i in the data set D. Gain ratio is a modification of the information gain that reduces its inherent bias towards features that can take on many distinct values. It applies a normalization to the information gain which penalizes a large number of subsets D_j. This normalization value is called the *Intrinsic Value* (IV) of a split and is calculated as

$$IV(x) = \sum_{j=1} \frac{|D_j|}{|D|} log_2 \frac{|D_j|}{|D|}$$

The Gain Ratio GR is then calculated as follows:

$$GR(x) = \frac{IG(x)}{IV(x)}$$

The features with the highest gain ratio are finally selected as splitting features. To select the best set of features that gives the maximum accuracy for each model, we examine different threshold values including 0.001, 0.005, 0.009, 0.01, 0.05 and 0.09. The results of this step explained in more detail in Section IV.

IV. EXPERIMENTS AND EVALUATION

We experimentally evaluate the performance of our proposed need detection method on the psychological human need data set. The experiments are designed with the goal of measuring the effectiveness of the three models of our framework: RNC, INT and MNS models. A set of experiments were conducted to analyze and validate the importance of different textual, psychological, and Twitter-specific features in recognizing an individual's need. The experimental settings and results are described below.

A. EXPERIMENTAL SETTING

The psychological human need data set was divided into 70% for training and 30% for testing while preserving the class distribution. For the classification algorithm, we use a Support Vector Machine (SVM). We adopt the Least Square Errors (LSE) SVM with a linear kernel and L2 regularization implemented in LIBLINEAR.[4] Since the second and third layers are multi-class classification tasks, we use the one-versus-all binary classification strategy. The model performance is evaluated using the metrics of F-score and accuracy. While conducting the experiments, we followed an incremental feature selection approach. We comparatively evaluated the predictive power of including each distinct feature and report the obtained result before and after any feature addition, both as a set and individually.

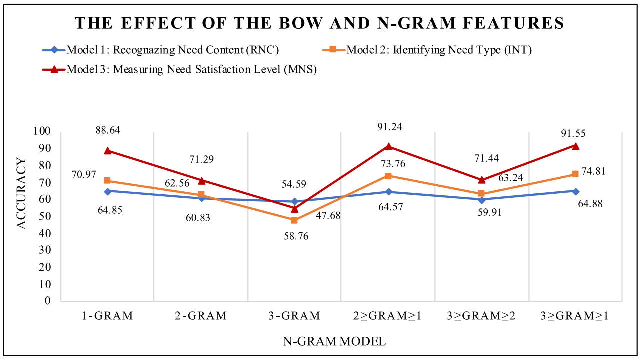


FIGURE 4. The effect of different n-gram features on the accuracies of RNC, INT and MNS models.

B. EXPERIMENTAL RESULTS

1) THE EFFECTIVENESS OF RECOGNIZING NEED CONTENT (RNC)

We first study the impact on the model's performance of the different textual features BoW and n-gram models including unigrams, bigrams and trigrams both individually and in combination. The graphical comparison in Fig. 4 shows their effect on the models performance. As we can see from the graph, combining unigrams, bigrams and trigrams yields the best performance with 64.88% accuracy. Next, we analyze the impact of the LIWC psychological lexicon, the emojis and the number of hashtag features on the model performance. Table 3 shows the accuracy and F-score for the tweets with need content class (TWNC) and tweets without need content class (TWONC).

As Table 3 shows, the model achieved 67.05% accuracy using only LIWC feature, 67.09% using LIWC feature combined with emoji features, and 65.48% using LIWC feature combined with the n-gram model. The frequency of emoji seems to be very slightly beneficial to the model. By combining all the features, the model achieved 64.81% accuracy, which is a lower accuracy when compared with the

[4]https://www.csie.ntu.edu.tw/ cjlin/liblinear/

TABLE 3. F-score and accuracy of Recognizing Need Content (RNC) model using different features.

Feature Types	#Features	F-TWNC	F-TWONC	Accuracy
LIWC	92	0.55	0.73	67.05%
LIWC + Emojis	93	0.55	0.73	67.09%
LIWC + $3 \geq gram \geq 1$	24011	0.58	0.71	65.84%
LIWC + $3 \geq gram \geq 1$ +Emoji + Hashtag Number	24013	0.57	0.69	64.81%

accuracy achieved with individual features due to the large number of features used. The problem of data sparsity and high dimensionality is solved using the GainRatio method. Out of the 24,013 features, we consider the most predictive features. This leaves us with 2526 features when using a threshold value of 0.01 as shown inTable 6. Eliminating the useless features has boosted the accuracy by 13.9 percentage points (pp) as shown in Fig. 5.

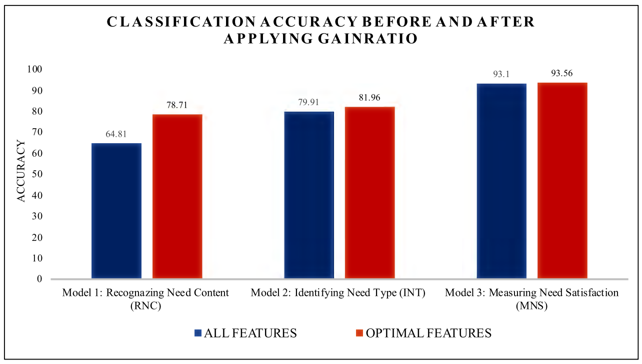


FIGURE 5. Models accuracy before and after selecting the most predictive features using GainRatio.

2) THE EFFECTIVENESS OF IDENTIFYING NEED TYPE (INT)

The experimental results with textual features show that the combination of the unigrams, bigrams and trigrams achieved better results, with 74.81% accuracy than when using any of the n-grams individually, as Fig. 4 shows. In Table 4 the results of the other features are listed. For psychological features, as can be seen from the Table, using the LIWC lexicon, the model achieved an accuracy of 68.28% whereas combining LIWC with the LCM lexicons (DAVs, IAV, SV) increases the accuracy from 68.28% to 68.82% (by 0.54 percentage points). Adding the number of hashtag features slightly increases the accuracy by 0.11 percentage points. Using the emoji features, including the frequency of emoji, the categorized emoji and the colored emoji increase the accuracy by 1.1 pp. The combination of all the features gives the maximum accuracy of 79.91%, with an absolute accuracy gain of 9.88 pp. After selecting the best 1893 features out of 9500 total features using GrainRatio, the accuracy increases to 81.96% as shown in Table 6 and Fig. 5.

TABLE 4. **F-score and accuracy of Identifying Need Type (INT) model using different features.**

Feature Type	#Features	F- Relatedness	F- Competence	F- Autonomy	Accuracy
LIWC	92	0.76	0.66	0.60	68.28%
LIWC + LCM (DAVs, IAV, SV)	95	0.75	0.70	0.59	68.82%
LIWC + LCM (DAVs, IAV, SV) + Hashtag Numbers	96	0.75	0.70	0.59	68.93%
LIWC + LCM (DAVs, IAV, SV) + Emoji + Hashtag Numbers* + Categorized Emoji + Colored Emoji	110	0.77	0.69	0.61	70.03%
LIWC + 3≥gram≥1	9482	0.79	0.81	0.74	78.44%
LIWC + 3≥gram≥1 + LCM (DAVs, IAV, SV) + Emoji + Hashtag Numbers + Categorized Emoji + Colored Emoji	9500	0.81	0.84	0.73	79.91%

TABLE 5. **F-score and accuracy of Measuring Need Satisfaction (MNS) model using different features.**

Feature Type	#Features	F- SNeed	F- DisSNeed	F- NCNeed	Accuracy
LIWC	92	0.80	0.76	0.56	72.10%
LIWC + Emojis + Sentiment Emojis + Categorized Emoji + Colored Emoji	109	0.80	0.77	0.56	72.41%
LIWC + NRC+ Opinion Lexicons	96	0.80	0.76	0.55	71.52%
LIWC + NRC + Opinion Lexicons + Sentiment Emojis + Categorized Emoji + Colored Emoji	113	0.80	0.77	0.57	72.57%
LIWC + 3≥gram≥1	9473	0.90	0.91	0.94	92.21%
LIWC + 3≥gram≥1 + NRC + Opinion Lexicons + Sentiment Emojis + Categorized Emoji + Colored Emoji	9494	0.92	0.91	0.95	93.10%

TABLE 6. **Average F-score of RNC, INT and MNS models using the optimal features.**

Need Models	Threshold	#Features	Average F-score
RNC model	0.01	2526	0.78
INT model	0.05	1893	0.82
MNS model	0.05	4117	0.93

3) THE EFFECTIVENESS OF MEASURING NEED SATISFACTION MNS

Based on the comparison graph for BoW and n-gram models in Fig. 4, the highest accuracy was achieved when combining unigrams, bigrams and trigrams, whereas, when using those models individually, the results presented the lowest accuracy. As illustrated in Table 5, using the LIWC psychological lexicon, the model performs well and gives an accuracy of 72.10%. Combining the LIWC with the NRC and the opinion sentiment lexicons gave a poor performance. However, including the sentiment, the categorized and the colored emoji features increase the accuracy slightly by 1.05 pp. A high performance is achieved when combining all the features where the model achieved 93.10% accuracy. Applying the feature selection technique, the most predictive features with a threshold of 0.05 gives the highest accuracy of 93.56% as shown in Table 6 and Fig. 5.

V. FLORIDA SHOOTING EVENT

The online phase of the proposed psychological need detection formwork could be utilized in a wide range of applications with diverse contexts (e.g. analyzing well-being on a daily basis, measuring need satisfaction level regarding a specific event or life aspect, or developing need-based recommender system). Based on the application objective, the microblog posts of interest will be gathered using Twitter search API.[5] As explained in Fig. 6, the microblog posts includes the textual and visual content will be retrieved with its metadata (i.e., posting time and geographical location). The multimodal data or, the post interactions data

[5]https://developer.twitter.com/

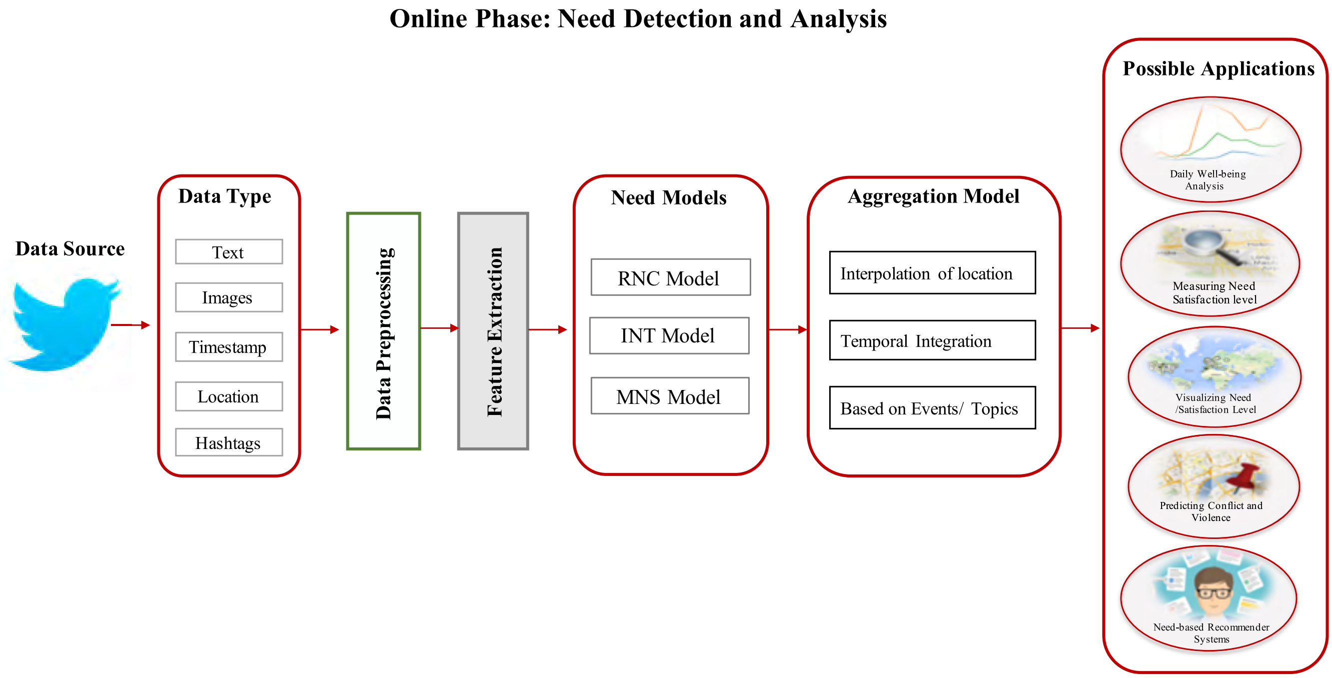


FIGURE 6. An overall flow diagram describing the online phase for the human need detection framework.

(which consists of retweets, replies and favorites) are also considered for each post. Each microblog post is represented as a tuple consisting of the following: a unique identifier of the tweet T_{id}, a unique identifier of the publisher U_{id}, a tweets textual message T_m, a tweet entity (i.e., images) T_e, a tweet posting location T_l, a tweet posting time T_t, the number of times the tweet has been retweeted T_{rt}, the number of replies to the posted tweet T_r, and the number of times a tweet is marked as a favorite T_f. The textual data will be preprocessed and the features will be extracted following the same steps in the offline phase. After automatically identifying the psychological needs using the three need models, the post interaction data (T_{rt}, T_r and T_f) and metadata (T_l and T_t) will be used to aggregate and represent the results.

We present a use-case scenario where we applied our proposed psychological need detection formwork to analyze and measure an individual's need satisfaction level in response to critical and violent situations. We examine the public reaction to the recent shooting event which occurred in a school in Florida on Wednesday, February 14, 2018. Seventeen students were killed by a single student shooter. The event reached trending topic level on Twitter just a few hours after the tragedy had occurred. We obtained the publicly available tweets under the hashtag #FloridaShooting, which characterized the event. To enrich our data coverage further, and obtained tweets with the least amount of excess noise, we also included other hashtags such as: #FloridaSchoolShooting, #Florida Shooting, #Florida, #StonemanShooting, #ParklandShooting, #SchoolShooting, #FloridaHighSchoolShooting. The collection revealed a total of 73,535 tweets from 49,621 users. We filtered out non-English tweets, non relevant tweets and tweets which contained links alone. We finished with 52,166 tweets. This final set of tweets went through the same pre-processing and feature extraction as those in the learning phase. Following these steps, the Recognizing Need Content (RNC) model was applied. A total of 43,956 tweets were classified as having need content. They were further classified based on the need type using the Identifying Need Type (INT) model and the satisfaction level using the Measuring Need Satisfaction (MNS) model. The aggregation of the result will be selected based on the application type. Thus, in this case, we aggregate the results based on temporal distribution.

In order to understand the public reaction and study the changes in the need satisfaction level throughout the shooting event, it is necessary to track the dynamic evolution event. We believe that time factor plays an important role in describing the event evolution and reveal the event's temporal changes. Therefore, we generate a timeline-based textual and visual representation to describe the event and highlight the important moments within the event. Since hashtags are considered to be the user-driven method for categorizing tweets regarding specific topics, we use them to identify the active sub-topics discussed during the entire event. We single out and examine the most frequently used hashtags appearing in tweets associated with the event main hashtags over all four days. The top ten most utilized hashtags for all four days are presented in Table 7, and are sorted in descending order according to frequency of use TF.

We study the most significant and frequently used words among the tweets in order to determine the theme of the tweets and recognize the key aspects (cause and consequence

TABLE 7. The top ten most frequent hashtags during the Florida shooting event.

Wednesday	Thursday	Friday	Saturday	March For Our Lives Event
1.#TalkAboutItNow 2.#GunControl 3.#Broward 4.#GunControlNow 5.#LoveisLouder 6.#Prayers 7.#MassShooting 8.#RIP 9. #ThoughtsandPrayers 10.#Condolences	1.#GunControl 2.#GunControlNow 3.#Islam 4.#Poor 5.#NRA 6.#PrayForDouglas 7.#America 8.#PolicyandChange 9.#GunReformNow 10.#NRABloodMoney	1.#GunControl 2.#FBI 3.#GunReformNow 4.#GunControlNow 5.#MAGA 6.#NikolasCruz 7.#Trump 8.#SecondAmendment 9.#StandYourGround 10. #NRA	1.#ThrowThemOut 2.#GunControl 3.#GunReformNow 4.#GunControlNow 5.#NRA 6.#NikolasCruz 7.#GunReform 8.#FBI 9. #StudentsDemandAction 10.#EndGunViolence	1.#NeverAgain 2.#NRA 3.#GunControl 4.#NaomiWadler 5.#BlackLivesMatter 6.#GunControlNow 7.#EnoughIsEnough 8. #GunReformNow 9.#EmmaGonzalez 10. #VetsVsTheNRA

clues) of the sub-topics that were discussed. After eliminating digits, punctuation and stop words, we plot the top 50 word collections as word clouds, which are then ordered by descending term frequency *TF* score. The size of each word cloud is proportional to the frequency of each word's occurrence. Word clouds for all the four days of Florida shooting are plotted in Fig. 9 and Fig. 10.

Visual information is useful in compensating for the lack of descriptive power of short texts. Therefore, we generate a timeline-based visual representation of the event to easily convey the atmosphere and show what words cannot completely express. In creating the timeline-based visual representation, we utilized the popularity-based ranking strategy previously used in [41]. When we compute the importance score of each single image, we only consider relevance and popularity. Diversity and coverage are not considered since we do not concentrate on summarization problems. The popularity of a single image has been defined and measured using different factors based on various contexts and platforms [42]. In measuring an image's popularity, we consider the social attention factors of images that attract the audience. After deleting non-relevant images, we calculate the social attention score (S_{attSco}) for each day of the event based on the following equation:

let i be the index for the T_{id} and assuming we have n T_{id}.

$$S_{attSco} = \sum_{i=1}^{n}(T_{rt} + T_f + T_r)_i$$

Where T_{rt} the number of times an image is posted or retweeted, T_f the number of times an image is marked as a favorite, and T_r the number of replies to the posted image. A high social attention score can indicate the popularity and importance of a particular image. For each day of the event, all images are ranked based on the popularity score and the top ranked ones are considered for visual representation. Fig. 11 shows the top four images ranked in descending order based on their social attention score over the four days of Florida Shooting event and the March for Our Lives event.

The analysis shows that the most pronounced need is relatedness with 67.57%, the autonomy need then follows at 11.9%, and competence need trails at 6.53%. Fig. 7 shows

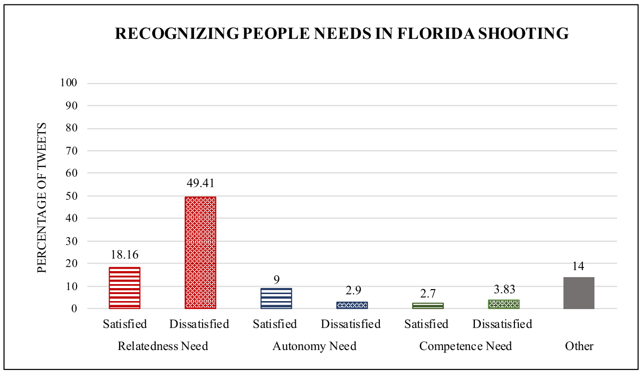


FIGURE 7. Identifying people's need and measuring their satisfaction level during the day of Florida shooting and the subsequent three days using our framework.

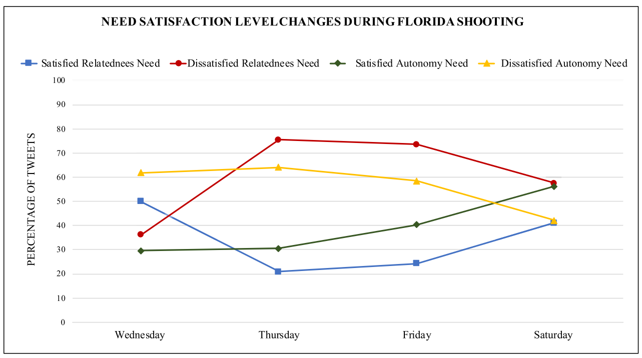
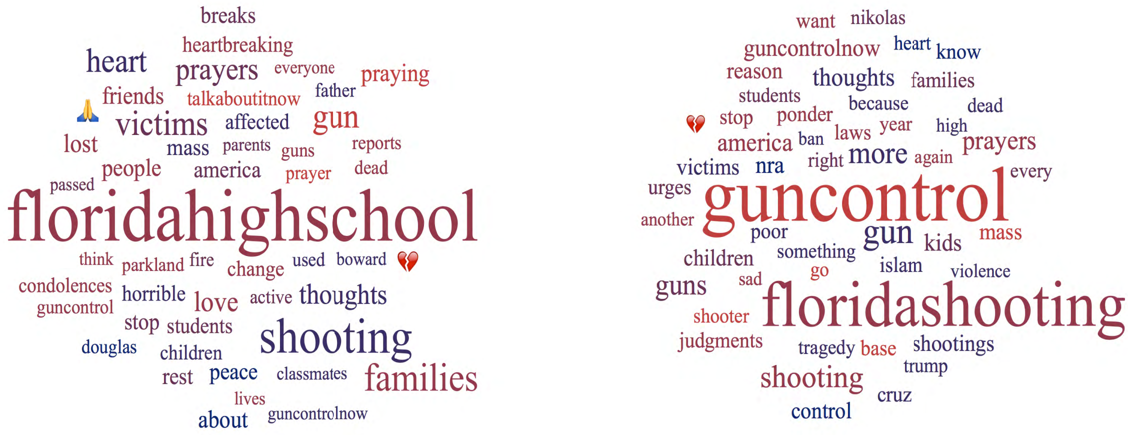


FIGURE 8. Measuring the changes in need satisfaction levels during the day of the shooting and the subsequent three days.

the overall need satisfaction level for the identified need types of autonomy, relatedness and competence throughout the event. As we can see, the analysis reflects a high dissatisfaction level of the relatedness need with 49.41% among the other need types.14% of the tweets were not considered for measuring satisfaction levels because they contained mixed emotion types. These were therefore classified as unclear and non-conducive tweets. We are focusing on analyzing the changes in satisfaction level of the relatedness and autonomy needs since they are the prominent needs expressed over the event. Fig. 8 illustrates the changes of the relatedness



(a) (b)

FIGURE 9. Word cloud generated from tweets posted on Wednesday Feb, 14 (a) and Thursday Feb, 15 (b).

(c) (d)

FIGURE 10. Word cloud generated from tweets posted on Friday Feb,16 (c) and Saturday Feb,17 (d).

and autonomy need satisfaction levels during the day of the shooting and a period of three days following the event. On Wednesday, the day of the shooting, we expected that a significant amount of tweets would reflect dissatisfaction or frustration in regards to the relatedness need since it is a violent event. However, deeper analysis shows that on that day, 50% reflected satisfaction regarding the relatedness need, compared to 36.2% whose tweets reflected dissatisfaction with respect to relatedness. The remaining 13.8% of the tweets were not considered because they were not clear. For the autonomy need, the majority of tweets expressed a dissatisfied need with 61.9% while 29.6% of them reflected a satisfied need.

As Table 7 shows, on Wednesday, the day of the shooting, people started talking about the event using the #TalkaboutItNow and #Broward hashtags. Moreover, the sub-topics were centered around outpouring emotional hashtags such as #LoveisLouder, #Prayers, #RIP, #ThoughtsandPrayers and #Condolences, which illustrates the thematic focus of the tweets sent on the first day. As illustrated by the word cloud (a) in Fig. 9, words such as ''families'', ''prayers'', ''victims'', ''thoughts'' and ''hearts'' were featured in a large number of tweets. As we can see in Fig. 11 (a), images with emotional reactions (sympathy and compassions) are the leaders in the image collection on this day. People expressed their emotions, prayers and condolences to the victims' families, which satisfies their relatedness need in terms of feeling connected to others (i.e., students and the victims' families), and explains the reason behind the high satisfaction level in relatedness need during the shooting day. The following tweets were collected on the Wednesday:

- *''Praying for all the families & friends of the victims of this horrible shooting love one another #parklandschoolshooting'' - Satisfied relatedness need*

(e)

FIGURE 11. **A chronological visual representation for Florida shooting event and March for Our Lives event. (a) Top ranked images posted on Wednesday Feb, 14. (b) Top ranked images posted on Thursday Feb, 15. (c) Top ranked images posted on Friday Feb, 16. (d) Top ranked images posted on Saturday Feb, 17. (e) Top ranked images posted during March for our lives event.**

- *"The blood of every victim is on your hands. DO SOMETHING! THIS IS SICK THAT YOU CONTINUE TO FIGHT GUN CONTROL. YOU ARE COMPLICIT !! #guncontrol #FloridaHighSchool #RyanIsResponsible #McConnelIsResponsible" - Dissatisfied relatedness need*
- *" These school shootings just make me more eager to become a teacher and do my part in never letting this happen again! #ParklandSchoolShooting #floridahighschool #standstrong" - Satisfied competence need*
- *"No child should go to school afraid of being killed. No child should go to school afraid, period. we NEED gun control #ParklandSchoolShooting " - Dissatisfied competence need*
- *"when is enough going to be enough? how many innocent people - how many innocent kids, have to lose their lives in order to catch your attention that a change in policy needs to happen? any change, just anything to stop these tragedies. #FloridaSchoolShooting " - Dissatisfied autonomy need*
- *"Florida rise up. hate will never win! #FloridaHighSchool" - Satisfied autonomy need*

On Thursday, the day after the event, the number of tweets reflecting a satisfied relatedness need dropped considerably from 50% to 20.9% and did not rise significantly over the next 24 hours. On this day, as can be seen from Table 7, gun control is a leading sub-topic of discussion within the #GunControl, #GunControlNow, #GunReformNow, #NRA, #NRABloodMoney hashtags, which embodies a growing sense of unrest and a significant spikes of frustration around 75.52% in regards to the relatedness need. This is also reflected by the public's disbelief and anger over the frequency of such tragic events, which is expressed through words such as "control", "stop", "another", as can be seen from word cloud (b) in Fig. 9. The visual representation in Fig. 11 (b) shows how images reflecting sympathy and compassions are later overshadowed by new images reflecting anger and instigating action. The following tweets were posted on Thursday:

- *"Wake Up America! We NEED sensible and REAL #GunControl! No one should have access to an "AR-15". No one;'(" - Dissatisfied autonomy need*
- *"I find it a blessing not to live in the United States! #parklandshooting" - Satisfied autonomy need*
- *"@SenSchumer, @NancyPelosi, @SenGillibrand, @SenBillNelson, @senmarcorubio - you guys can't let up this time. We can't just talk about #GunContril for 1 news cycle and then forget about it. It's time for #GunContolNow!! #SchoolShootings #ParklandShooting" - Dissatisfied relatedness need*
- *"@RobertwRuncie: I want to thank everyone in the Broward community and around this country...there is a GoFundMe account that's been set up...Stoneman Douglas Fund #ParklandShooting" - Satisfied relatedness need*
- *"i'm 15 and im terrified to go to school everyday. i constantly worry if a shooting will occur at my school #ParklandShooting" - Dissatisfied competence need*
- *"So we can all agree that praying isn't working now right? I am open to plan b. #ParklandShooting #GunControlNow" - Satisfied competence need*

On Friday, the third day, the analysis shows no notable reduction of dissatisfaction of the public relatedness need, which is expressed in 72.45% of the tweets and in the autonomy need which is expressed in 58.45% of the tweets. On that day, the gun control hashtags were more heavily used than on the previous day, which indicates the focus of discussion. Moreover, as Table 7 shows, there are some new hashtags emerging, such as the #FBI, #MAGA, #SecondAmendment and #StandYourGround, which may indicate an alarmingly consistent level of dissatisfaction in public needs. People used words such as "gun", "shooter", "victims", "FBI" and "Trump" more frequently, as shown by the word cloud (c) in Fig. 10, which reflects the focus of public conversation and discourse on that day. Examples of tweets discussing these topics are listed below:

- *"The only people you need to blame #floridahighschoolshooting is the #FBI they r the ones who screwed up wonder why all of their resources r going to trying to destroy @POTUS on a fake investigation" - Dissatisfied relatedness need*
- *"Thinking about and praying for the brave educators who saved children's lives. Heroes ?? Thank you !!! #floridahighschoolshooting #gratitude" - Satisfied relatedness need*
- *"Walk Out of School to Demand Safer Gun Laws LINK #floridaschoolshooting #walkout #students" - Satisfied competence need*
- *"I try to stay out of politics but the #floridahighschoolshooting just makes my blood boil. I gather its actually the 18th #HighSchoolShooting so far this year! Do #Americans /really/ not see how stupid it makes them look to the rest of the world?Really??? #GunContolNow" - Dissatisfied competence need*
- *"WE CAN DO WHATEVER WE WANT! UNITED WE STAND. DIVIDED WE FALL. AND GET SLAUGHTERED! #GunControlNow #GunReformNow We've amended the Constitution before, it's time to do it again! Reform or I'll vote to ban completely! #CNN #floridahighschoolshooting #MSNBC" - Satisfied autonomy need*
- *"Education should not be underlined with gun terror. Enough is enough! #StudentsForRegulation #floridahighschoolshooting" - Dissatisfied autonomy need*

As we notice from the second example, some tweets expressed a satisfied relatedness need, which explains the slight increase on this day. As the visual representation in Fig. 11(c) shows, image depicting positive emotions towards a teacher who saved student lives achieved the most social attention. This might be the reason behind the slight increase in satisfied relatedness need.

Due to the frustration around the relatedness and autonomy needs in the previous days, disquieting public reactions of conflict and disagreement lead to requiring immediate actions from authorities. As can be seen in Fig. 11(c) and (d), Images requiring actions were among the top ranked images on the Friday and Saturday. New trending sub-topics demanding action emerged on Saturday, the fourth day after the shooting.

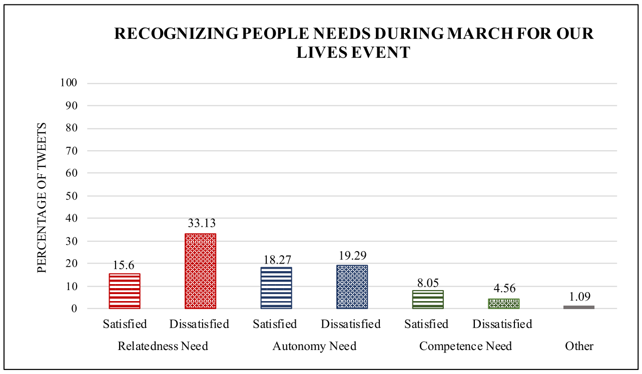


FIGURE 12. **Identifying people's need and measuring their satisfaction level during March For Our Lives event.**

For example, the hashtags #ThrowThemOut, #StudentsDemandAction and #EndGunViolence were among the top 10 most used hashtags, as Table 7 shows. The word cloud graph (d) in Fig. 10 shows words such as "leaders", "laws", "safety", "change", "refuse", "commonsense" and "violence", used by the public, which indicate the climate of public dissent reflected within the sub-topics.

The analysis shows how unmet needs can cause conflict over the second and the third days. As illustrated by human need theories such as Nonviolent Communication theory [20], needs are fundamental; individuals and groups will do whatever it takes to attain their basic needs, even engage in verbal and physical violence if they see no alternative. Thus, on the fourth day, we observed people starting to connect and take action in order to satisfy their need [43]. For example, thousands, including students across the US, were walking out to protest against gun violence and support Florida high school students and other victims of the same type of violence. Moreover, #MarchForOurLives was born, a new hashtag intended to plan and schedule a major event spearheaded by students taking action because they no longer want to risk their lives waiting for authorities to make a move. The rise and call to action may explain the slight increment in some people's satisfied autonomy (56.3%) and relatedness need (41.2%), as pictured in Fig. 8. Tweet examples from the Saturday collection are listed below:

- *"Sick of leaders doing nothing to fight gun violence? So are we. Let's work together and #ThrowThemOut #floridahighschoolshooting" - Dissatisfied relatedness need*
- *"Teens speaking truth to power regarding the need for #GunControl after #Parkland. They are hero's and there voices won't be silenced" - Satisfied relatedness need*
- *"Things we've already solved: Putting seatbelts in cars. Preventing the next train crash. Cars reminding us not leave our babies in the backseat. Things we've haven't solved:#2A #GunReform #SaturdayMorning" - Satisfied competence satisfied*
- *"Having anxiety being in the #UF Library, although medal detecters, what does that even do if someone*

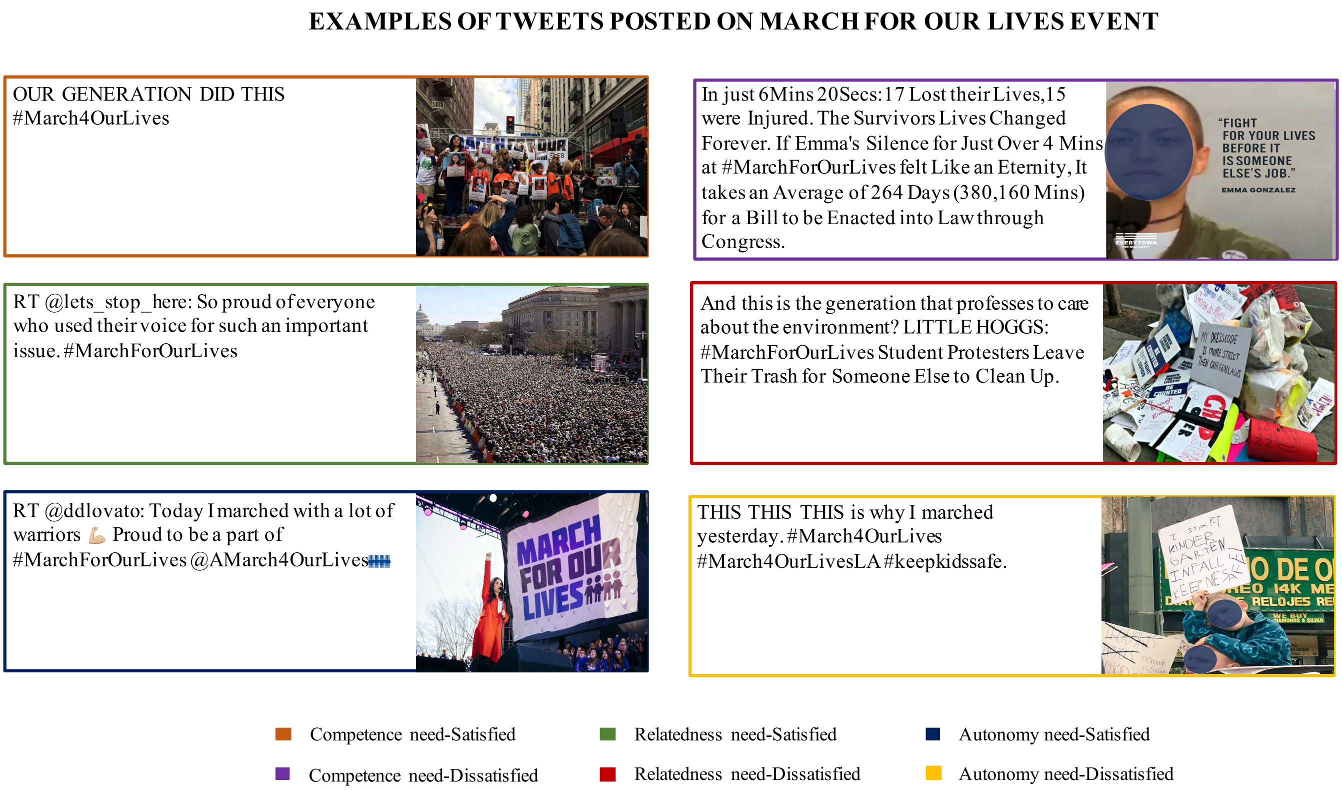


FIGURE 13. Random examples of tweets posted during March For Our Lives event classified using our proposed framework.

shoots up the place? I'm 33 and have learned to cope with #anxiety but I can't imagine being a teen and dealing with this #mentalhealth #FloridaSchoolShooting very sad #NoGuns" - Dissatisfied competence need

- *"Flight is booked! See you soon #Florida! You can support my investigation into the #FloridaSchoolShooting here LINK" - Satisfied autonomy need*
- *"It's time to walk out. #FloridaSchoolShooting" - Dissatisfied autonomy need*

We analyze and measure the need satisfaction level of individuals at the beginning of the shooting event and during the conflict situation. We also aim to analyze and measure their satisfaction level after the initiation of a movement or action taken toward satisfying their needs. In this respect, we analyze individuals' needs during the scheduled March for Our Lives event, which took place on Saturday, March 24. The event, led by student survivors of the shooting event, demanded action against gun violence and supported better gun control. We used the #MarchForOurLives hashtag to collect tweets about the event from March 24 until March 28; we then analyzed them using the online phase. After applying the RNC model, a total of 33,376 tweets were classified as having need content. They were further classified based on the need type and the need satisfaction level using INT and MNS models. The analysis results aggregated based on the March for Our Lives event as overall. The analysis in Fig. 12 shows 42% of the tweets express positive need satisfaction, while 56.98% of the tweets reflect dissatisfaction in relation to people's needs. Satisfaction increased by 12.14% in this particular event, in comparison to the beginning of the shooting event, as depicted in Fig. 7. The demand for immediate action could contribute to this increase, where #NeverAgain is the most frequent hashtag used during this event, see Table 7. Other hashtags such as #NRA, #GunControl, #BlackLivesMatter, #GunControlNow, #EnoughIsEnough,#GunReformNow and #VetsVsTheNRA were among the top 10 most used hashtags which reflect the thematic focus of the tweets. Relatedness is the most prominently indicated need, representing 48.73% of the collected tweets, followed by autonomy need, which is also heavily expressed in this event at 37.56%, and finally, competence need makes up the rest at 12.61%. As Fig. 12 shows, individuals express autonomy and competence needs during the course of this event at a higher rate when compared to those expressed at the beginning of the shooting event. As mentioned in Section III, autonomy is defined as the willingness to do something, and competence is defined as the ability to interact with the environments effectively and dealing with challenges. This might explains the increase in the number of tweets which express autonomy and competence needs. Furthermore, as reflected by the analysis results, images that show students in action, pertinent signage

FIGURE 14. Word cloud generated from tweets posted during March For Our Lives event.

and any dynamic protest atmosphere were among the top ranked images over the duration of these events as shows in Fig. 11(e). As illustrated by the word cloud in Fig. 14, new words such as ''movement'', ''support'', ''protest'', ''amendment'', ''speech'', ''never again'', ''generation'' and ''proud'' were among the top 50 frequent words, which indicates the overall climate and focus of event. These new words describe an empowered and determined sentiment among people and in regard to their actions and state of mind during this event, which may reflect the reason behind the growing number of tweets expressing autonomy and competence needs. Fig. 13 shows tweets combined with images posted during the March for Our Lives event classified using the proposed framework.

VI. CONCLUSION

In this work, we propose an automatic detection framework to identify individual needs and measure their satisfaction level utilizing users' published social media contents. The framework consists of three need models for recognizing need content, identifying need type and measuring need satisfaction levels. In developing the models, we explored various linguistic, psychological and Twitter-based features. We experimentally evaluated the performance of our proposed models on a psychological need data set which was annotated manually by psychologists. The models obtained encouraging results in identifying an individual's needs and measuring the satisfaction level during critical events. Estimating the percentage of people in a community experiencing need dissatisfaction would be used as an early warning for conflict and violence requiring quick action from authorities [20]. The three need models could potentially be employed in a large variety of other applications such as marketing and recommendation scenarios, monitoring daily psychological well-being, measuring need satisfaction levels with regard to various life aspects and living conditions [44]. The framework could be further enhanced by incorporating techniques such as topic modeling and named-entity recognition to detect and specify the causes of satisfaction and dissatisfaction levels automatically. Moreover, to further our research, we plan to explore how predictive other social media content such as images, videos, and external web-pages are when analyzing and inferring people's needs.

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