Recognizing Human Needs using Machine Learning-powered Psychology-Based Framework

by

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Abstract

Recognizing the basic needs of individuals can provide the root explanations for their feelings and help predict their behavior, as explained by the Human Needs Theories (HNT). Comprehension in regards to citizen needs in the context of a smart city improves situational awareness and could guide authorities in decision making processes, facilitating effective planning for the future. Accordingly, we aim to shed light on public reaction towards political, religious or terrorism events in regard to psychological needs by adopting the new form of sensing which employs the idea of utilizing citizens, themselves, as "soft sensors", in the hopes of creating a powerful tool for deciphering the temperament of a population.

In this thesis, we propose a psychological need recognition framework which consists of several modules, including data collection, data preprocessing, feature extraction, and contextualization. The proposed framework utilizes a theoretical-based multi-layered reference model that is based on research in the field of motivational psychology. We use the constructed layers of the proposed reference model to identify an individual's basic psychological needs, measure their need satisfaction level, and assess their social surroundings in various aspects of life. We introduce a psychological needs dataset, which is a collection of social media content annotated by psychologists based on each layer of the reference model. Several techniques are employed to encourage high-quality annotations. We design and develop need classification and regression models, with each corresponding to one of the predefined concepts that form the theoretical layered reference model; namely: 1) Need Content Recognition (NCR) model, 2) Need Type Identification (NTI) model, 3) Need Satisfaction Level Measurement (NSM) model, 4) Social Context Evaluation (SCE) model, and 5) Life Aspect Identification (LAI) model. For a more comprehensive and deeper analysis, the Frustrated Need Intensity Estimator (FNIE) model and the Satisfied Need Intensity Estimator (SNIE) model are developed to determine the intensity score of the satisfaction level.

Over the process of developing the classification models, we conduct many experiments to explore and compare the effect of different preprocessing steps and data preparation techniques. We evaluate the predictive powers of various textual, psychological, semantic, lexicon-based and twitter-specific features. In order to provide benchmark results, we compare and evaluate the performance of diverse machine learning algorithms for recognizing psychological needs. Our results confirm the effectiveness of the developed psychological needs models.

The proposed framework is engaged to recognize individuals' needs, measure their satis-

faction level and evaluate their surrounding environment in response to two critical events: the Florida shooting event, which occurred on February 14$^{\text{th}}$, 2018, along with the related March for Our Lives event which followed on March 24$^{\text{th}}$, 2018, and the New Zealand terror attacks which occurred on March 15$^{\text{th}}$, 2019.

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List of Acronyms

ICT Information and Communication Technologies
WHO World Health Organization
HNT Human Needs Theories
LIWC Linguistic Inquiry and Word Count
SMOTE Synthetic Minority Oversampling Technique
NCR Need Content Recognition model
NTI Need Type Identification Model
NSM Need Satisfaction Level Measurement Model
SCE Social Context Evaluation Model
LAI Life Aspect Identification model
FNIE Frustrated Need Intensity Estimator Model
SNIE Satisfied Need Intensity Estimator Model
IG Information Gain
GR Gain Ratio
UGC User-Generated Content
SDT Self-Determination Theory
BNT Basic Needs Theory
NVC Non-Violent Communication Theory
MNB Multinomial Naive Bayes Algorithm
SVM Support Vector Machine Algorithm
LR Logistic Regression Algorithm
RF Random Forest Algorithm
K-NN K-Nearest Neighbors Algorithm
DT Decision Tree Algorithm
NPN Neural Process Network
REN Recurrent Entity Network
LSTM Long Short-Term Memory
CNN Convolutional Neural Network
IRR Inter-Rater Reliability

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Chapter 1

Introduction

1.1 Introduction

Urban innovation and solutions driven by Information and Communication Technologies (ICT) have been progressively applied to enhance urban life in terms of economy, mobility, environment, people, living and governance. The realization of a true smart city vision is now closer than ever [79]. More and more, the number of applications and services that are adopting these technologies with the intention of improving the performance of urban services which will, in turn, enhance the quality of life of citizens, is growing [48]. For these applications to be effective, a variety of sensors are needed in order to continuously collect near real-time data. Currently, urban planners in a smart city rely mostly on the data obtained from measurement equipment or physical sensors "hard sensors" such as cameras, environmental sensors, implanted medical devices, or telematics systems in vehicles [106]. The data retrieved from the deployed sensors is inserted into a large computing platform and then aggregated to provide a unified view of the city. Authorities then reference this data in making informed decisions on the management of the city and its events. The data retrieved from hard sensors, however, does not directly reflect the fluid response of people regarding changes in their immediate surroundings at any given time. According to [48], engaging citizens in city planning and the development process is considered to be paramount in the evolution of smart cities, and, therefore, should be one of the main objectives when considering how to proceed. Moreover, in [19], Coe *et al.* mentions that encouraging the citizens' participation in the decision-making process could lead to more democratic communities. Conclusively, more attention to the interaction between humans and urban space is called for in order to drive a more effective and relevant decision-making process. Thus, the idea of utilizing the citizens themselves as "soft sensors" has emerged. The evolution of social media has provided a previously unparalleled source in collecting data on human interaction and, as such, has attracted considerable interest in this field lately. As social media platforms continue to evolve, they have become the most valuable, reliable and easily accessible data source which reflects how people perceive their surroundings.Their perception always depends on a variety of dynamic and static context factors. People use social media platforms to present themselves to the world and share their observations about their surrounding environment in real-time, primarily in the form of text and other supported media such as images and videos. They broadcast their activities and observations, sharing their opinions about a wide variety of topics and events. This rich content has garnered the interest of smart city researchers, as it generates numerous possibilities for developing large-scale temporal and geographical analysis applications within different domains. For instance, Twitter data has recently been used to leverage new political information and predict election results [106], analyze public opinions regarding a political candidate [17], as well as in the exploration of different political standpoints [17]. It has also been used to cover crucial events such as reporting an attack [101] and recognizing criminal content [112]. In terms of real-time awareness, Twitter has been utilized as a data source in monitoring local and global happenings [30], gathering information about disasters and earthquakes [43], and capturing individual real time responses during disasters [101] and environmental emergencies [43]. In essence, it is not practical to simply consider analyzing when, where and what people are doing in the city in terms of their activities and behaviour. It is more important to know how they feel by recognizing their emotional responses toward happenings in the city, in order to affect appropriate decision-making processes in the best interests of the city and its population. This raises the idea of an Affect-Aware city [41]. As explained in Figure (1.1), this city is able to understand, interpret and adapt to the affective states of its citizens, referencing their emotions, moods, and personality traits. Citizens' diverse affective states can be decoded and utilized in urban planning as a complement to the use of traditional hard sensors in evaluating ongoing planning processes, supporting decision making, and providing additional insights regarding the city's inhabitants in order to create a big picture of the city's live state. Citizen affective states would be accessible through various data sources that are available in a smart city, as illustrated in Figure (1.1). User-Generated Content (UGC) from multiple social media platforms is one of these data sources. UGC is a continuous stream of collectively sourced information that is comprised of a vast amount of personal data, including users' daily thoughts, insights, evaluations, feelings, and emotions, expressed through their geographic and time-based textual status

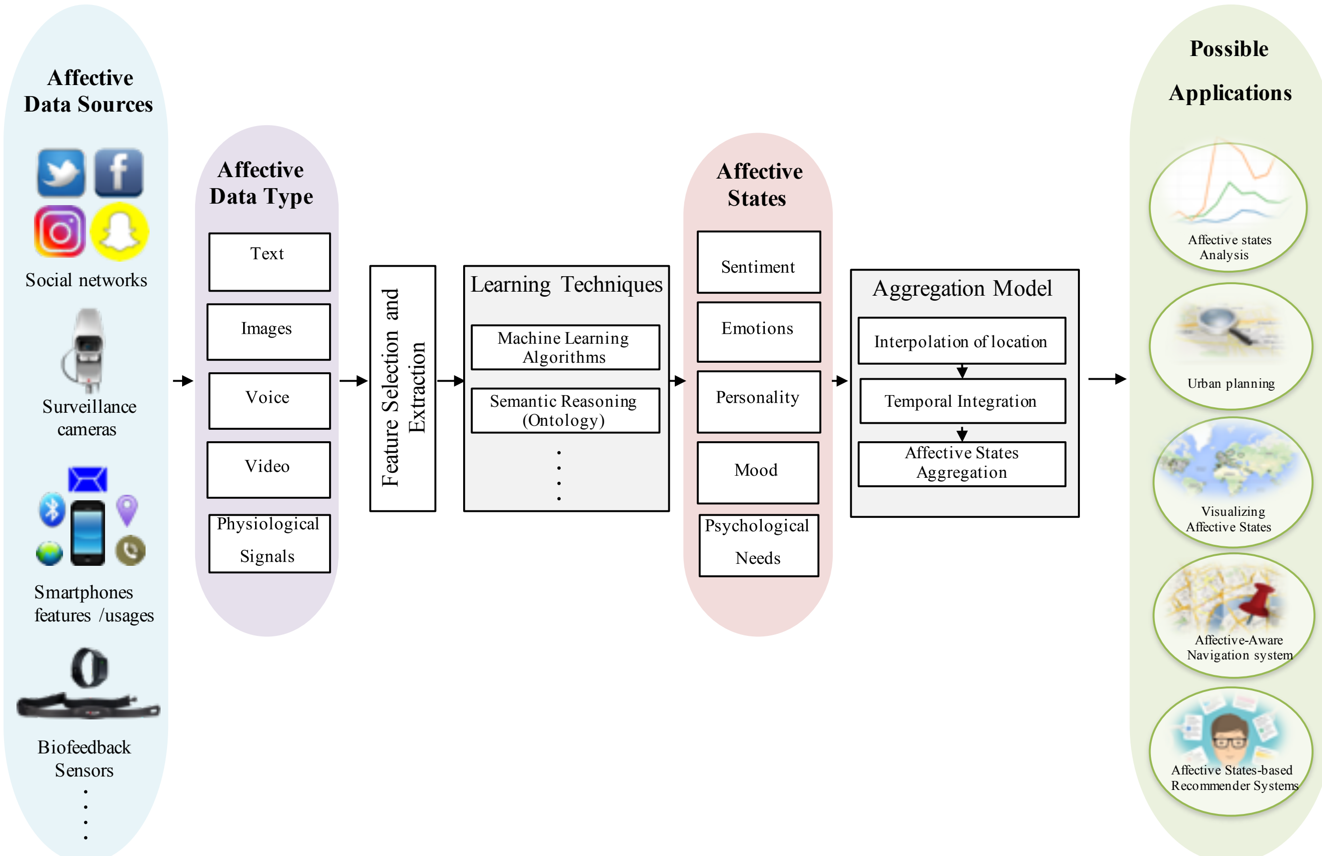


Figure 1.1: The vision of the Affect-Aware City [41]

updates. UGC is considered a rich source of information that can be used to reveal individuals affective states, and, as a result, researchers have begun mining this massive resource of affect data for this purpose. For example, a large part of the existing research focuses on general dimensions sentiment analysis and opinion mining, under three polarity categories: positive, negative and neutral [77], [57] using lexicon-based methods and machine learning algorithms. Some studies go beyond the general sentiment analysis, recognizing distinct and dimensional emotional categories [7], [114] with the help of psychological lexicons. Certain recent studies have also explored more distinguishable long-term affective states such as personality [40] and mood [10], using psychological psychometrics. As we review previous works, we realize that recognizing a population's diverse affective states is practical and achievable when taking advantage of the wealth of social media content that is constantly changing in a dynamic fashion, based on local and global happenings. The interpretation of this data could have a large impact, assisting authorities, city planners and decision makers in detecting positive or negative trends developing within the city, evaluating the effectiveness of policy making in important city issues, and achieving real time awareness during critical events in order to take early countermeasures. Despite the recent focus on analyzing *"how"* people feel in a city by determining their distinctive affective states (emotions, personality and mood), the exploration around the *"why"* behind these feelings, actions and behaviors has, to date, received very little attention. Given this, our goal is to shed the light on the importance of recognizing and analyzing individuals' psychological needs, since they are viewed as the main motivation behind their emotions and subsequent behaviors.

1.2 Motivation

Violence is one of the leading causes of death worldwide. Based on the World Health Organization (WHO) report, each year, an estimated 1.6 million people worldwide lose their lives, directly or indirectly, as a result of violence [58]. This is over 4,000 people dead every day. Others are left injured, or suffer from physical or mental health problems. Moreover, this violence is costing countries billions of dollars each year. Based on Centers for Disease Control and Prevention report[1], in the United States, the total cost of interpersonal violence (financial, human, physical and emotional) is more than \$300 billion per year, while the lost productivity as a result from violence amounted to \$318 billion. Investing early in preventing conflicts at the source and avoiding escalation into violent crises is 60 times more cost effective than post-violence reconciliation.

Understanding the causes behind violence among humans could be the first step in avoiding conflict and preventing the resulting destruction from happening. Human Needs Theories (HNTs) offer valuable insights into the primary causes of conflict and the origin of violence, claiming that unmet needs are what leads to unrest, which can escalate into violence [13]. HNTs provide root explanations of human feelings, and, in turn, what motivates an individual's actions and behavior in various situations [68]. HNTs have been applied in various contexts, such as psychology, economics, health care, sociology, politics and philosophy. A definition of need from a social science perspective, according to Christian Bay, is: *"Needs shall refer to any requirement for a person's survival, health, or basic liberties; basically meaning that, to the extent that they are inadequately met, mental or physical health is impaired. Thus, "need" refers to necessities for not only biological survival but also for health and development (physical and mental growth) of persons as human beings"* [9]. Another definition of needs, from a political science perspective, states *"Human needs are a pow-*

[1] https://www.cdc.gov/injury/wisqars/index.html

erful 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" [92]. Within the field of psychology, needs are defined as the underlying layers that cause emotions and feelings, which can later empower and direct human behaviors and activities.

The main theoretical premise behind all the HNTs is the understanding of the implicit underlying motivations that affect a broad range of behaviors, and define many actions across various situations [98], [105]. Behind every action, by every person, every time, there is a hunger to meet one or more of these healthy needs. Basic human needs, as argued by humanistic psychologists, are fundamental, stable, and universal, across all cultures, gender and ages [65], [109] and [8]. The satisfaction of fundamental human needs is essential to promote personal growth and well-being, and, also, to avoid serious harm. Thus, all human actions and behaviors are strategic attempts to meet the underlying needs. Otherwise, the unsatisfied and frustrated needs can cause conflict and lead some people to behave violently and exploitatively [33]. Rosenberg states, *"Violence is a tragic expression of unmet human needs. It occurs when individuals or groups do not see any other way to meet their need, or when they need understanding, respect and consideration for their needs"* [8]. He has proven this theory, as applying the HNT to the conflict in Chechnya was considered to be an effective strategy in the process towards a sustainable and peaceful resolution [56].

At our most basic core, we, as human beings, desire a good life. Taking this into consideration, individual needs must be the heart of a successful and efficient smart city. Simply utilizing innovative technologies by a city does not make it smart, directly. The adaption of technology so that it enhances quality of life factors in balance with people's needs should be the goal of a city in order to be considered as a smart city.

Being aware of citizen's needs, within a smart city, can provide the root explanations of their motivation underneath their upsets, confusions and complaints. This awareness can be utilized by city planners and decision makers to adapt the city's services and plans to reduce struggle, conflict and to avoid violent reactions. Accordingly, our objective is to illuminate the vast benefits of automatically recognizing citizen needs. To the best of our knowledge, there is no existing work that recognizes human needs from a psychological well-being perspective. Therefore, in this thesis, we propose an automatic, low-cost, large-scale, non-intrusive human need recognition framework, utilizing natural language processing techniques, computational linguistics and artificial intelligence to identify human psychological needs, measure their satisfaction levels, evaluate their surrounding environment around different life aspects during any subjective event or towards emerging topics at any time, and in any location, using their publicly available social media content.

1.3 Research Problems

Despite the fact that many works have shown the importance of analyzing social media content in regard to different affective states, exploring and analyzing citizen basic needs have, to date, received very little attention. Understanding and analyzing citizen needs can provide the root explanations of their feelings and help predict their future behavior. Therefore, our intention is to shed the light on the importance of understanding the causes of citizen emotions and the underlying motivations behind their actions. However, individual needs are typically assessed using approaches from psychological science [59]. Due to many limitations, these traditional approaches are now considered inadequate for large-scale need detection and analysis. The following points highlight some of these limitations:

- Traditional assessment methods are very time consuming.
- They are limited to a small group of respondents, which will only reflect a small percentage of the entire population within a city or community.
- They are impractical when analyzing individual needs frequently in an interactive way within a large group (i.e. community).
- Most human need psychometric surveys are designed with respect to one specific life aspect (i.e. relationships, work, etc.), and cannot be used to reflect multiple life aspects [107] and [55].
- They cannot efficiently capture the dynamics and context that embodies need experiences.

All of these limitations are considered to be barriers to analyzing millions of individual needs. Consequently, these traditional need assessment methods are insufficient for large-scale need detection and analysis. On the other hand, UGC in social media provides us with a valuable opportunity to analyze people's psychological needs in an unobtrusive and scalable way. Despite the recognized potential of social media platforms like Twitter as a data source for analyzing human needs, the few existing works that explore social media content in regard to human needs have some drawbacks and limitations:

- There is no psychological need dataset that is publicly available to use.

- None of the existing works explore human need from a psychological well-being perspective.

- Some of the existing works do not utilize or incorporate human need theories or have psychological base knowledge.

To overcome these limitations, we develop a theoretical-based recognition framework which utilizes the dynamic nature of social media data to recognize individual psychological needs and assess their satisfaction levels in large scale venues such as cities and communities.

1.4 Contributions

- Propose a theoretical based multi-layered reference model for psychological need recognition that is guided by research in the field of motivational psychology. The layers of the reference model are constructed to identify psychological needs, measure their respective satisfaction level, and assess the individual's surrounding environment in various aspects of life.

- Construct a psychological needs corpus: a collection of social media posts annotated manually by psychologists based on the reference model's layers.

- Design and develop the following need recognition models:

1. Need Content Recognition (NCR) model to recognize need content.
2. Need Type Identification (NTI) model to identify the type of psychological need.
3. Need Satisfaction Level Measurement (NSM) model to determine the satisfaction level.
   (a) Design and develop intensity estimator models: SNIE, FNIE to determine the intensity score of the satisfaction level.
4. Social Context Evaluation (SCE) model to evaluate individual's surrounding environment.

5. Life Aspect Identification (LAI) model to identify the life aspect within the need experience.

- Use the proposed framework to recognize the needs of individuals and measure their related satisfaction levels in response to the Florida shooting event, which occurred on February 14^{th}, 2018, and the related March for Our Lives event on March 24^{th}, 2018, as well as the New Zealand terror attacks (March 15^{th}, 2019).

1.5 Scholarly Achievements

In the process of completing this work, the following publications have been submitted, accepted or published:

- **Journal Papers:**

- Rajwa Alharthi and Abdulmotaleb El Saddik "A multi-layered Psychological-based reference model for citizen need assessment", IEEE ACCESS, Submitted

- Rajwa Alharthi, Benjamin Guthier and Abdulmotaleb El Saddik "Recognizing Human Needs during Critical Events using Machine Learning Powered Psychology-Based Framework", IEEE ACCESS, 2018

- Rajwa Alharthi, Benjamin Guthier, Camille Guertin and Abdulmotaleb El Saddik "A Dataset for Psychological Human Needs Detection From Social Networks". IEEE ACCESS, 2017

- Rana Abaalkhail, Benjamin Guthier, Rajwa Alharthi and Abdulmotaleb El Saddik "Survey on ontologies for affective states and their influences", Semantic Web, 2017

- Raneem Alharthi, Rajwa Alharthi, Benjamin Guthier and Abdulmotaleb El Saddik "CASP:Context –Aware Acute Stress Prediction System", Multimedia Tools and Applications, 2016

- **Conference Papers:**

- Rana Abalkial, Fatimah Alzamzami, Samah Aloufi, Rajwa Alharthi, Abdulmotaleb El Saddik "Affectional Ontology and Multimedia Dataset for Sentiment Analysis" , International Conference on Smart Multimedia (ICSM), 2018s

- Benjamin Guthier, Rana Abaalkhail, Rajwa Alharthi, Abdulmotaleb El Saddik "The Affect-Aware City", in 2015 International Conference on Computing, Networking and Communications (ICNC), 2015.
- Benjamin Guthier ,Rajwa Alharthi , Rana Abaalkhail , Abdulmotaleb El Saddik "Detection and Visualization of Emotions in an Affect-Aware City" Emerging Multimedia Applications and Services for Smart Cities, 2014

1.6 Thesis Outline

The remainder of the thesis is organized as follows:
Chapter 2
Section 2.1 presents an overview of the background literature which recognizes distinct affective states in social media content. Section 2.2 reviews some closely related works in recognizing human needs, detailing the goal of the work, the method they used and the achieved result. It provides a comparison between the surveyed works and our framework, based on various important characteristics. Based on the finding, the chapter concludes by providing a set of design requirements.
Chapter 3
This chapter discusses the design of theoretical-based multi-layered reference model. Detailed information about the need concept and the psychological theories that are used to construct each layer are presented. The Chapter also describes the process of constructing our psychological need dataset. A description of the annotation process, the provided guideline, and the designed annotation tool are provided in detail. An assessment of the annotation agreement among psychologist judges is presented. The statistical analysis of our collected dataset with some examples of the annotated tweets is given in this chapter. Sample tweets from the annotated dataset which illustrate various aspects of the theoretical-based reference model are provided.
Chapter 4
This Chapter explains the process of designing and developing the psychological need models. It also introduces the preprocessing and feature extraction modules. The features employed to construct the models are illustrated in detail. The sampling techniques used, the normalization and the dimensionality reduction steps are described.
Chapter 5
This chapter presents the experimental setting and the evaluation metric used. The effectiveness of each classification and regression model is demonstrated through insightful

discussions. A comparison between the selected machine learning algorithms are provided while experimenting each feature set. The model's performance after applying the dimensionality reduction techniques is reported.

Chapter 6

This chapter describes a variety of potential applications using the psychological need recognition framework. Two case studies are introduced as further proof-of-concept for the framework. Data related to critical events: Florida shooting event 6.1, March for our lives event 6.2 and New Zealand terrorist attacks 6.3 is collected and analyzed using the framework. It is concluded by providing a discussion based on the findings, which illustrate the usefulness of our framework.

Chapter 7

The final chapter contains the conclusion which summarizes the work presented in this thesis. There is also discussion of limitations, remaining issues for further study, and recommendations for future work.

Chapter 2

Background and Related work

2.1 Recognizing Human Affective States

Using social media data, many researchers have detected and analyzed different types of human affective states.

- Sentiment

A considerable amount of prior research has been directed towards general sentiment analysis, which has typically focused on recognizing the polarity dimensions. Pak *et al.* [77] have explored the approach of using happy and sad emoticons to create a corpus that automatically labels 300,000 Twitter posts and divides them into positive or negative classes. For the neutral class, he used objective tweets from newspaper accounts. In a similar work [57], Kouloumpis *et al.* demonstrates their method of combining hashtags with emoticons to automatically label tweets. They selected the top hashtags that reflected the sentiments of the tweets and considered them as labels. Other work studied specific types of sentiments expressed in Twitter [22]. They manually labeled 3,852 hashtags with five different sentiment categories, namely: strongest sentiment, most likely sentiment, context-dependent sentiment, focused sentiment and no sentiment. They then used the hashtags and 15 smileys as labels for the sentiments.

- Emotion

Several studies have attempted to provide an in-depth analysis of distinct and dimensional emotion categories. In [7], they manually labeled a corpus of 8,150 tweets with Ekman's six basic emotions: anger, disgust, fear, joy, sadness, and surprise, as well as with an additional category of neutral. A similar work also created a corpus consisting of 7,000 tweets, manually annotated with Ekman's six basic emotions as well as the love emotion [91]. The tweets in their corpus were collected using a specific predefined list of 14 emotional topics such as #Christmas and #Valentine's Day. Other works investigated an automatic method for emotion labeling using hashtags for self-annotation. Purver *et al.*, in [82], used two different predictable markers: emoticons and hashtags, to retrieve and explicitly label tweets with Ekman's six emotions. Following the same method, in [70] Mohammad *et al.* introduced a corpus called the Twitter Emotion Corpus (TEC) consisting of 20,000 automatically labeled emotional tweets. Most of the identification studies were based on the six basic emotions originally proposed by Ekman for facial expressions, which limits the richness of the actual human emotional experiences in text . Researchers in [114] aimed to explore all the possible emotions expressed in tweets with no predefined list of categories or specific psychological models. They presented a 5,553 tweets corpus that was annotated manually with 28 distinct emotion categories.

Some researchers have also begun to deeply understand emotions by investigating their dimensionality. For instance, the authors in [49] used hashtag-based labeling to automatically label 134,000 tweets with two-dimensional space: Valence and Arousal, as proposed by Rusell's Circumplex Model. Other works used Plutchik's dimensional model and automatically labeled 5.9 million tweets with eight basic bipolar emotion categories [102]. Other recent work assigned four dimensions, based on the Fontaine model (pleasantness, arousal, dominance and unpredictability), to 24 emotion hashtags and created a dataset with 58,000 tweets [42].

- Mood

In regards to long-term affective states, there are few existing works that capture and analyze human moods based on social media. For example, in [10] the construction of their corpora of 9 milions tweets, they matched terms from the Profile of Mood States POMS-ex instrument, which include six dimensions of moods: tension, depression, anger, vigor, fatigue and confusion to tweets. Choudhury *et al.* [20] used the Circumplex Model and manually identified 203 mood indicator words and used them as hashtags to create a 10.6 million tweets dataset. In [23], researchers manually created a mood lexicon containing 172 terms and linked them to the 11 affections of PANAS-X: fear, sadness, guilt, hostility, joviality, self-assurance, attentiveness, shyness, fatigue, surprise, and serenity. Using the mood terms as hashtags, they collected 6.8 million tweets labeled with 127 moods and 11 affects.

- Personality

Twitter data and social behaviors have been used to predict the five personality dimensions: openness, conscientiousness, extroversion, agreeableness and neuroticism. In [40], they collected public tweets along with social activities for 71 users who had taken the big-five personality test, in order to study the correlations. They found that social behavior on Twitter, including: network bandwidth, message content, pair behaviour, reciprocity of actions, informativeness and homophily could be a strong indicator of personality traits.

2.2 Recognizing Human Needs

2.2.1 Recognizing Human Needs using Conventional Methods

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) [96]. 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.

2.2.2 Recognizing Human Needs through Social Media

Few attempts have been made to infer people need recently. They differ in their objective, theoretical background, dataset used and their methodology as can be seen from Table (2.3) and Table (2.4). We explain each work in details clarifying their limitations and shortcomings in both the theoretical background and the recognition method.

IBM Research group [115] 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 psychometric (instruments) that identify the needs that influence purchase behavior; they developed their own needs psychometric using Ford's needs model, which proposes a needs classification inspired by the Maslow hierarchy of fundamental needs [109]. Ford's model includes 12 needs categories that correlate and explain consumer behaviour, namely: structure, practicality, challenge, self-expression, excitement, curiosity, liberty, ideal, harmony, love, closeness and stability. In the psychometric test, participants from the United States 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 which is the Maslow hierarchy of fundamental needs [109] that was used to build their model was restrained by its cultural and hierarchical limitations [53]. 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 [65], 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 (2.1) shows examples of tweets expressing closeness and ideal needs.

Table 2.1: Tweet examples for closeness and ideal needs from the IBM need dataset [115].

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.."

In other work, Ghazi *et al.* address the problem of recognizing the causes of emotions from a linguistic perspective [38]. They explore the detection of the causality in emotional expression and phrases. They build a first English dataset[1] 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.

Table 2.2: Examples of emotions and causes from the work of Ghazi *et al.*[38] work.

Emotions	Sentence	Causes
Anger	"Yet she still finds herself full of frustration and anger towards him"	"towards him"
Shame	"You see, I'm just as a shamed of all this as you are."	"of all this"

They only focused on the explicit expression of causes which are captured within the spans of text, referring to the emotion stimulus words, and/or the sequence of the words. In the first example in Table (2.2) , the phrase expresses the emotion anger, and the classifier detects the phrase that explains the cause of the emotion, which is "towards him". The second example conveys the emotion shame, and the clause, "of all this", is recognized as the emotion stimulus. 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.

Consider another mental state modeling work, proposed by Rashkin *et al.* [86]. This work endeavors to understand the mental states of the actors in a simple story based on an event they experience. They proposed a dataset consisting of 15,000 commonsense stories[2], which were manually labelled under emotion and motivation categories, using crowdsourced workers from Amazon Mechanical Turk. While annotating, they examine the step-by-step causal dynamics interaction between story characters and delineate the mental states for each character, based on the events they experience. They applied motivation categories inspired by Maslow and Reiss' motivation theories, and for emotions they referenced Plutchik's basic emotions model. During the annotation process, they found that the annotators were not familiar with motivational theories, and therefore, found it challenging when assigning motivation categories to the dataset. As a result, while all are annotated for emotions, only a third (5000) of their annotated stories are additionally labelled under motivation categories. The annotators are also asked to provide a free

[1]http://www.site.uottawa.ca/ diana/resources/

[2]https://uwnlp.github.io/storycommonsense/

text describing what causes the character's behavior. To determine the actor motivation, they give the classifier a character and a line of the story including all the related context lines which mention the character. A logistic regression model is trained on TF-IDF, Neural Process Network (NPN), Recurrent Entity Network (REN), Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) encoders. The best model performance achieved a 35.23 micro F_{score} using their proposed story dataset, and attained a score of 64.8 when trained on the open text explanation provided by annotators using TF-IDF schema. Their classifier was most effective at predicting Maslow's physiological needs and Reiss's food motives only because they both have clear indication from the text. Their approach is designed based on long, formal stories and considers the multiple interactions between story characters.

Ding *et al.* in [31], attempt the classification of sentences in personal stories from weblogs based on seven human needs. Their work shows numerous shortcomings in both the theoretical background and the classification method. Not only did they fail to provide a concrete theoretical guideline in defining the needs categories, they also did not consult an expert prior to proposing their taxonomy of needs and performing their annotation process. They claim their work was inspired by two human need theories: Maslow's Hierarchy of Needs and Fundamental Human Needs theories; however, their proposed need categories do not show any connection to either of those need theories. To illustrate, they defined the Freedom need category as "freedom of movement and accessibility:" (1) the need to move or change positions freely; (2) the need to access things or services in a timely manner". Here are some examples of freedom need category within their dataset: "I have been waiting for 5 hours", and, "I was stuck in my car". Based on both the Maslow's Hierarchy of Needs and Fundamental Human Needs theories, freedom need means self-esteem, determination, equal rights, freedom of speech and freedom of expression which, neither of these statements reflect. Likewise, the following two sentences: "I woke up at 2am", and, "I bought a house" are two more examples from their labelled dataset. The first sentence was labelled as a negative event, and the second sentence as a positive event; however, both sentences clearly characterize neutral sentiment. There is no clear indication of any emotional clues from the sentences' authors which could lead them to being classified as either positive or negative. It is very important in the annotation process to have a clear context in order to label the sentences with an accurate polarity category. Another flaw lies in the fact that they associate the concepts of basic human needs with desires, wishes and goals, which are considered separate concepts and unique entities in most psychological need theories.
Moreover, within their process, the number of items in their dataset (approximately 559) is not sufficient for a classification task involving more than nine classes. This may explain

Table 2.3: A comparison between existing works and our proposed psychological human need recognition framework.

		Knowledge base			Annotation Process	
Reference work	Research goal	Psychological theory/model	Need concept	Need categories	Annotation guidline	Annotation method
IBM research group [115]	Identifying user needs that influence punches behaviour.	Ford's needs model [4] inspired by Maslow hierarchy of fundamental needs [109].	Identify need type (marketing practice-oriented classifications)	Structure, practicality, challenge, self-expression, excitement, curiosity, liberty, ideal, harmony, love, closeness and stability	-Developed their own needs psychometric -360 Participants wrote about products wished to buy and their needs	-Constructed dataset automatically using product names -Labeled tweets with need categories that match product names.
Ding *et al.* in [31]	Categorizing events based on the affective reasons	-Maslow's Hierarchy of Needs [109] -Fundamental Human Needs [65]	Identify need type	Physiological needs, health needs, leisure needs, social needs, financial needs, cognition needs, freedom needs + Emotions and opinion	Three human annotators	Manually
Rashkin *et al.* [86]	Tracking mental states of story characters (motivations and emotional reactions).	-Maslow's Hierarchy of Needs [109]. -Basic motives of Reiss [88]	Identify need type	-Needs: self-esteem, spiritual growth, physiological needs, love and stability -19 motivation categories -Eight basic emotional dimensions	Crowdsourced workers from Amazon Mechanical Turk.	Manually
Ghazi *et al.* [38]	Detecting the causality in emotional expression	-Ekman's six emotions [34]	-	-	Build a dataset annotated with emotion and stimulus using FrameNet's emotions-directed frame	Automatically
Our proposed psychological human needs recognition framework	Providing a comprehensive psychological need analysis	-Self-determination macro theory [25] -Basic psychological need theory [108], [16] -Evaluating Social context [27]	-Recognize Need content -Identify need types -Measure need satisfaction level -Evaluate social context, -Identify life aspects	-Recognize need content (NCR) -Identifying need type (NTI): Relatedness, Competence, Autonomy -Measuring need satisfaction level (NSM): Satisfied and frustrated -Social context (SCE): Supportive social context and Non-supportive -Identifying life aspect (LAI)	Annotated by psychologists based on a validated guideline	Manually

Table 2.4: A comparison between existing works and our proposed psychological human need recognition framework Count-.

	Dataset Description			Methodology	
Reference work	Data source	#instances	Availability	Classification approaches	Model performance
IBM research group [115]	-Surveys data -Twitter	-6 million tweets for ideal and closeness needs only -2587 survey responses	Not available	Supervised learning approach using linear regression model	-All Correlation values are bellow 0.50
Ding *et al.* [31]	Narrative story corpus	542 affective events (sentences)	Not available	Supervised learning using logistic regression	-The model achieved (54.8) accuracy -(62.4) average F_{score} in their updated work using event context
Rashkin *et al.* [86]	Simple commonsense stories	15000 short commonsense stories	Available	Logistic regression	-The model achieved: (35.23) micro is F_{score} using their dataset - (64.8) when trained on the open text explanation
Ghazi *et al.* [38]	Formal sentences	820 sentences	Available	A Conditional Random Field (CRF) model	The model achieved (81%) in detecting linguistic emotion stimulus
Our proposed psychological human needs recognition framework	Social media	18,847 tweets	Available	Supervised learning: SVM, MNB, LR, RF, K-NN and DT	-Accuracy for (NCR) model is (79.13) -For (NTI) model is (81.97) -For (NSM) model is (93.56) -For (SCE) model is (75.70) -For (LAI) model is (60.48)

the poor performance (54.8 average F_{score}) reflected in their results. In their subsequent follow-up work [32], they hypothesized that the polarity of most affective events arises from the satisfaction or frustration of basic human needs. They used the above classifier to label new events with need categories. They then combined it with another classifier which was designed based on event context to infer need category. The result of the combined classifiers improved to a 62.4 average F_{score}.

The limitations and the drawbacks of the existing works motivate us to develop our psychological-based framework to analyze social media textual data for basic needs concepts from a psychological well-being perspective. Therefore, in this thesis, we aim to automate the detection of psychological needs by proposing psychological need recognition framework that employs different need models. The models are developed based on a theoretical multi-layered reference model 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 conventional psychological measurement methods and transcend the limitations of existing works.

Requirements:

To overcome the limitation of traditional need assessment methods and existing related works, the design of the framework should satisfy the following set of functional requirements.

- The framework should be designed and structured based on well-known psychological need theories that have been verified and validated.

- The framework should provide comprehensive recognition of the basic need and its related concepts to fully analyze and interpret the need experience.

- The design of the framework should consider the dynamic nature of social media platforms, and the casual style of their content to carefully capture the context of need experience.

- The framework should be able to analyze needs for all individuals with no restriction, regardless of their age, gender, culture and religion.

- The framework should be able to recognize human needs in the major life aspects.

- The framework should provide the ability to recognize individuals needs any time, in any location, and during any type of event.

Chapter 3

Theoretical-based Multi-Layered Reference Model

3.1 Psychological-based Multi-Layered Reference Model

To develop the psychological-based multi-layered reference model presented in Figure (3.1), we utilized knowledge about human needs from several psychological theories as our foundation to form and structure the layers of the reference model [24], [21]. At the same time we explored publicly available posts from Twitter to reveal some connections between the multiple dimensions of an individual's basic needs and social media textual data using the iterative process. The following explains the psychological-based multi-layered reference model in details.

3.1.1 Layer 1: Recognizing Psychological Need Content

Layer 1 of the reference model is constructed based on the relationship between needs and emotions. Needs are similar to illnesses and medical conditions; they are invisible, yet they can be observed and detected by signs, which as most psychological need theories indicate, are emotions. As humans, our underlying basic needs are strongly correlated with emotions and feelings. The Self-Determination Theory (SDT), which is a broad theory of human motivation and one of the most widely accepted theories that concern human needs and personality traits, states that in our daily language, needs can be expressed through feelings and emotions which will later direct and motivate our behaviors and actions [25].

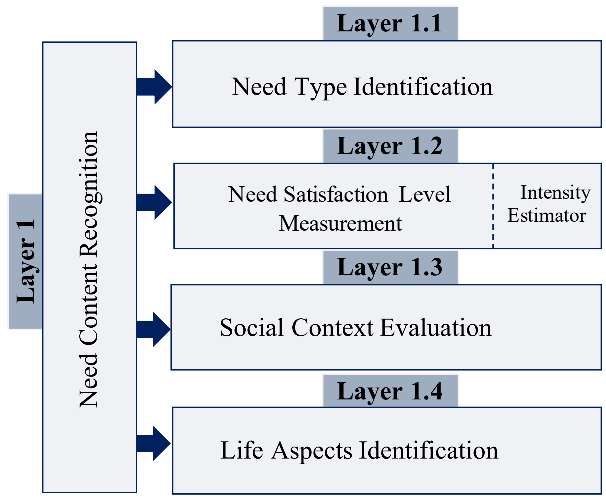


Figure 3.1: Psychological-based multi-layered reference model.

Therefore, the first layer aims to verify the emotional content, focusing on whether or not the social media textual data truly reflects the individual's emotional state. For instance: the tweet in the following first example has #emotional word, which is #Joy, but it does not express the author's feeling. It describes a movie called "Joy". On the other hand, the tweet in the second example truly expresses the author's emotion, which is happy. This layer filters out tweets with non-emotional content such as the first example and keeps only emotion related tweets that reveal information about the individual's emotional state such as the second example.

- "**#Joy** movie full of emotions 👌🏼"
- "I will relive this weekend forever and always. I've never been so happy in all aspects of my life. 😊 **#happy**"

3.1.2 Layer 1.1 : Identifying Psychological Need Type

Layer 1.1 is the core element of the psychological-basic reference model. It identifies the type of psychological needs that are present underneath emotional states. The objective of this layer is to consider the basic and fundamental needs that are required for an individual to feel satisfied, in order to promote well-being and prevent conflict and violence [18]. Therefore, it builds mostly upon the concepts of the SDT. One of the leading reasons to prefer this theory is that the Basic Needs Theory (BNT), which is a sub-need theory within the SDT framework, proposes psychological needs that are innate, fundamental, and universal. They can be applied to all individuals, regardless of their gender, age, culture, ethnicity, religion, or socioeconomic status which satisfy one of our design requirements [16]. This aligns well with our vision of analyzing the diversity of social media users and content. Moreover, the three needs proposed by the BNT have been recognized as true psychological needs among 10 candidates [95]. The three basic psychological needs categories used in this layer include the need for Autonomy, Competence, and Relatedness. The need for autonomy can be defined as the feeling of self-direction. Individuals need to experience a sense of willingness and need to take control of their own behaviour without any external pressure. The need for competence can be defined as the need to feel capable and effective while interacting with the environment. People need to adapt to the changing environment, master challenges, and learn different skills. Finally, the need for relatedness can be defined as a person's feelings of belonging, attachment and meaningful relationships with others, specifically, relationships with friends and family and with larger groups or communities (e.g. religious or political).

To the best of our knowledge, no psycholinguistic resources have been developed to explain the different ways in which individuals express their inner psychological needs (explicitly or implicitly) on social media using textual data. This has led us to design our annotation guideline based on the basic needs definitions and the existing psychometric scales that are traditionally used to measure needs. Each concept in the reference model has been explained with definitions, examples and with psychometric statements. The guideline are comprised of standard psychometric scales (general and domain specific scales) that were verified and validated by psychologists [24], [16]- [37]. The following tweets examples show some different ways in which individuals express their needs based on the second layer.
For autonomy need category:

- "I Hate My Life , I Hate My Self and I Hate All What I'm Dealing with #Hate"
- "I hate waking up early just for a freaking assessment at school 😒 😤 #annoyed"
- "I'm feeling myself... #excited"
- "Feeling vulnerable in many aspects of my life. Really need some #reassurance #affection #change"

For competence need category:

- "I am a girl with dreams and vision both! #independent #proud"

- "School, and after school job might kill me but I know I can make happen but ima be #Stressed😅"
- "Just love it when I achieve a goal I set myself #Determined 👊 💁"
- "I'm so disappointed in what I did in my demo teaching!! :(#Disappointed"

For relatedness need category:

- "When you request Sunday off and your boss makes you work. I'm done no more HWC for me Fml 😔 #Depressed"
- "Wish my friends wanted to talk to me. #Lonely"
- "I just wish I can be with him every second, minute, hour, day and for the rest of my life. #contented"
- "I'm so happy cause i found real and amazing friends in my life #Happiness #satisfied😊"

The emotion categories verified in layer 1 might give a clear suggestion of the underlying need [21]. For example, if someone feels lonely he/she might need to feel connected with others, which is linked to the need for relatedness.

3.1.3 Layer 1.2: Measuring Need Satisfaction Levels

Layer 1.2 is to measure the level of the satisfaction with the needs identified in the previous layer. The experienced emotions usually 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) [21], [25]. Thus, the polarity and the intensity of the emotions that are experienced help to determine the state of fulfillment of the needs. Also, more attention should be given to the emoticons since they are used frequently in Social media platforms to express emotions. The following examples show tweets with the categories of satisfaction levels they were given based on layer 1.2.
Social media posts (Tweets) from the satisfied need category:

- "I am a girl with dreams and vision both! #independent #proud"

- "I'm so happy cause i found real and amazing friends in my life #Happiness #satisfied 😊"

Tweets from the frustrated need category:

- "I Hate My Life , I Hate My Self and I Hate All What I'm Dealing with #Hate??"
- "Wish my friends wanted to talk to me. #Lonely"

Determining Need Satisfaction and Frustration Intensity Score

After identifying the need satisfaction and frustration levels in layer 1.2, our next goal is to determine the intensity of these levels in order to best understand the individual's experience. The intensity refers to the degree or strength of the emotions felt. Each emotional word used by individuals are associated with differing intensities. For instance, both depression and unhappiness belong to an emotion class which would be categorized as sadness; however, they qualify differently in their intensities, where depressed conveys a higher amount of sad emotion than unhappiness. Because we understand that human needs are directly related to an individual's underlying emotions, we scrutinize the magnitude of the emotions in identifying the intensity of the satisfaction and frustration level. In analyzing a tweet of a specific need satisfaction level (satisfied or dissatisfied), the goal is to determine the degree of need satisfaction or need frustration felt by individuals. The intensity level can be determined using qualifiable categories (i.e. low, moderate and high) or using real value scores ranging from 0 to 1. A score of 1 means highest satisfaction level, whereas a score of 0 means the lowest. The ability to automatically determine and measure the intensity of satisfaction levels can be beneficial in many need recognition applications. For example, an application that monitors an individual's psychological well-being could focus on detecting a significant need frustration in someone's life, and subsequently recommend an appropriate coping and healing strategy to prevent critical mental health issues such as depression or suicidal thoughts [13]. Another instance could be the early detection of high need frustration level in public reaction during any critical events or crisis could aid in determining appropriate and immediate action which could prevent possible conflict and violence that could arise amongst the chaos. Examples from different intensity categories for satisfied need:

- "Well i did hear once before that girls are attracted to men that look like their dad ! 👌🏼" - **Low intensity**

- "It's finally raining in Ashland Oregon. We've been parched all summer & fall. The plants & people are rejoicing! " - **Moderate intensity**

- "gardiner_love : Thank you so much Gloria ! You're so sweet and thoughtful ! You just made my day more joyful ! I love you too ! 😊 💕 " - **High intensity**

Examples from different intensity categories for frustrated need:

- "Life izn't about pleasing each others ... 😕 #hell #with" - **Low intensity**

- "People irritate me 😞 " - **Moderate intensity**

- "I have serious separation anxiety 😭 😭 💔 " - **High intensity**

3.1.4 Layer 1.3: Evaluating Social Context

Layer 1.3 has been constructed to evaluate the quality of the individual's surrounding environment in light of his/her human needs. This layer aims to assess and better understand the way different social contexts affect the individual's satisfaction level. The main theoretical premise underlying the construction of this dimension is that individuals require supportive environments to satisfy their basic psychological needs in order to promote personal growth and psychological well-being [27]. On the other hand, if an individual's surrounding environment does not nurture but instead thwarts their well-being, their basic needs will not be fulfilled and their emotional wellness will be affected negatively. Social contexts, which range from interpersonal relationships, such as family, friends and classmates, to more general settings and distal contexts such as social structures, cultural norms, values and economic and political systems, influence the availability of such supports. For every need experienced, this layer identifies the type of social context and determine whether it supports or thwarts the satisfaction of the need.

3.1.5 Layer 1.4: Identifying Life Aspects

Layer 1.4 in the reference model represents the various aspects and domains of an individual's life. Since basic needs must be satisfied across all life domains [68], we measure the needs satisfaction and evaluate the social contexts in nine life domains including: family, social relations, work, education, government, leisure, health, religion aspects and general evaluation. The following examples explain how we evaluate the social contexts in tweets

for different life aspects based on layer 1.3 and layer 1.4.
For supportive social contexts category:

- "You know that feeling of excitement you used to feel when going on a field trip? Yeah that's how I feel everyday at this job #satisfied 🚀 💵 " - **Work context**
- "God is really blessing me, it's overwhelming, but I'm ready, ready to put the work in? I'm ready. #Happy #Excited 😊" - **Religion context**

For Non-supportive social contexts category:

- "No charges for the #psycho cop who slaughtered #TamirRice. #shameful" - **Governmental context**
- "So the guy I like...pretend to liked me*sigh* ..hating life a lot... I feel like I'll never be happy again... #depressed" - **Social relation context**

3.2 Psychological Need Dataset

3.2.1 Data Collection

To build our corpus using social media content, we selected the Twitter microblog as our data source. Twitter is a dynamic platform where individuals frequently update their status to declare their thoughts, share their opinions and express their feelings and emotions. Moreover, Twitter data reflects the way individuals perceive their surrounding environment in real-time. Therefore, this user-generated content can be used as a source of data for a deeper understanding of the hidden motivations behind an individual's behaviors and actions. To collect the data to construct our corpus and reduce the number of useless and noisy tweets in the collection, we relied on the previously explained relationship between psychological needs and emotions. Therefore, we collected tweets that expressed emotions. To ensure our selection was accurate, we selected an appropriate emotional classification model that explores the nature of human emotions and encompasses all possible emotion categories. Thus, we adopted an emotional model that has conceptualized over 100 emotion categories into a three-level hierarchical structure: primary, secondary and tertiary [94]. The primary level contains the six basic emotions of love, joy, surprise, anger, sadness and fear. The secondary level contains a list of 25 distinct emotion subcategories of the six basic emotions. In the tertiary level, each secondary emotion is comprised of deeper emotion categories that vary in their intensities. For instance, the basic emotion sadness has distinct subcategories such as suffering, disappointment, and shame. The latter has even deeper emotions with different intensities, such as guilt, regret and remorse.

In the next step, we followed the methodology explained in [111] to obtain a collection of tweets that are automatically labeled with the above emotion categories. The use of hashtags has been proven by other studies, including [70] and [91] as an effective way of collecting tweets that are automatically labeled with emotion categories. All the emotion categories listed in the three levels of the emotional model were directly adopted and assigned to emotional hashtags, such as #surprise, and were then used as queries to collect tweets along with various synonyms and word tenses. For example, for surprise we used #surprise, #surprised and #surprising. Other frequently used terms were also added, for example #wow, which is used to express the emotion of surprise. We also retrieved tweets containing the emotional keywords as a part of the hashtags, like #StressedOut, #kindascared and #imsolonely.

The Twitter Search API[1] was used for the period of September 11, 2015 to December 31, 2015 to collect English-language tweets filtered by the predefined emotional hashtags. The search script ran daily at several different times for each emotion category, in order to obtain a wide variation of data. A total of 313,210 tweets posted by 170,202 different users were collected. Each collected tweet is combined with its metadata, explained in Table (3.1).

3.2.2 Data Preparation

To ensure data quality, we filtered out duplicate tweets, tweets with less than three words and tweets with more than three hashtags. This left us with a sample of 205,240 unique tweets. Because Twitter's textual data is unstructured and noisy, further filtering was performed to remove useless words (syntax elements) before the annotation process. For example, all usernames (@username) and URLs (links, images and videos) within a tweet were removed. Emoticons, punctuation marks (i.e., !!, ?) and social acronyms and abbreviations (i.e., b4 for before and BR for best regards) were kept since they are meaningful to emotion expression and are frequently used on Twitter due to the 140 character limitation. After all the above filters were applied, we randomly sampled approximately 18,847 tweets for our annotation process.

[1] https://developer.twitter.com/en/docs/tweets/search/overview

Table 3.1: The Notations used in the dataset and their descriptions.

Notations	Descriptions
User-ID	The official tweet's author
User-Name	The displayed name on the profile
Tweet-ID	The unique identifier of the tweet
Twitter-Message	Tweets textual data
Twitter-Timestamp	The day and time of posting the tweet
Tweet-Geo-location	The longitude and the latitude
User-Location	The location specified in the user's profile
Emoticons	Facial expressions in the form of icons
Hashtags	Hashags used to categorize tweets to a specific topics

3.2.3 Annotation Process

To encourage high-quality annotations, the process followed three stages. In the first stage, comprised of a few rounds, annotators underwent training sessions and collectively labeled tweet samples to ensure they fully understood the annotation process and the kind of annotations required. Since we are dealing with informal text from social media, we demonstrated each layer of the reference model using examples obtained from Twitter messages. An expert in SDT reviewed all of the examples in the annotation guidelines. To maximize the annotator's performance, we developed an annotation tool to apply the full annotation scheme and to increase the speed of the process. The tool displays the tweets, allowing the annotators to select from predefined categories. The primary researcher and two annotators from the field of psychology participated in the annotation process. Once the training sessions were completed, the process was clear and well defined, and all annotators agreed on the general standards.
In the second stage, which was an evaluation stage, all annotators were assigned the same set of tweets and asked to label them independently to assess their agreement. The annotators labeled each tweet displayed in the tool with the corresponding category from the annotation scheme, as explained before.

Inter-Rater Reliability

We assessed the Inter-Rater Reliability (IRR) to determine the degree to which annotators agreed with the assignment of the predefined categories specified in the annotation

Table 3.2: The average of the pairwise agreements and the Fleiss Kappa scores between the annotators.

Need Concepts (Layers)	Average Pairwise Agreements	Fleiss Kappa
Layer 1: Recognizing need content	90%	0.82
Layer 1.1: Identifying need type	89%	0.82
Layer 1.2: Measuring need satisfaction level	74.9%	0.64
Layer 1.3: Evaluating social context	72.5%	0.55
Layer 1.4: Identifying life aspects	57.7%	0.48

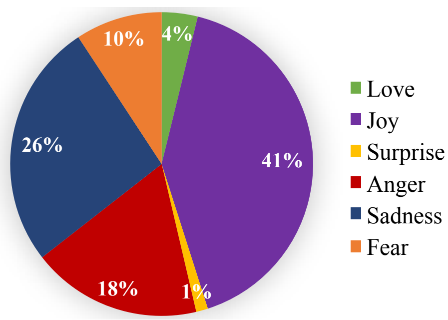
scheme to a subset of tweets by using two measurement methods. The first method is the average of the pairwise agreement between the annotators, presented as percentage as seen in Table (3.2). This method calculates the percentage of the data agreed upon by all the annotators. A matrix has been created in which the columns represent the three annotators and the rows represent a subset of tweets. The cells in the matrix contain the nominal labels for each tweet, as determined by the annotators. The percentage is calculated as the number of agreements in the annotations divided by the total number of the annotated tweets. In the second measurement, we utilized the Fleiss Kappa metric, which is a statistical method used widely to measure the agreement between multiple annotators in labeling many categories [36]. The Fleiss Kappa measurement not only calculates the percentile agreements, but also considers the possibility of agreements between annotators occurring by chance. The Fleiss Kappait is calculated using equation (3.1).

$$\kappa = \frac{Pr(a) - Pr(e)}{1 - Pr(e)} \tag{3.1}$$

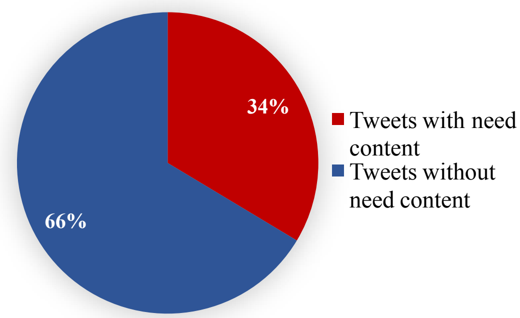
Where $Pr(a)$ denotes the actual observed percentage of agreement, and $Pr(e)$ denotes the probability of expected agreement due to chance. Kappa ranges from 0 to 1.0, with 1 reflecting perfect agreement and 0 reflecting agreement that occurs by chance.

Based on the reasonable agreements that were achieved between the annotators across all layers, it seems reasonable to move forward to the last stage, which is an independent annotation stage where each of the annotators were given a set of tweets to label it individually. In this stage, each annotator annotates a different subset of tweets that is randomly selected to maximize the number of instances in the dataset and reduce the load on each annotator. At the end of this stage, approximately 18,847 tweets were labeled manually.

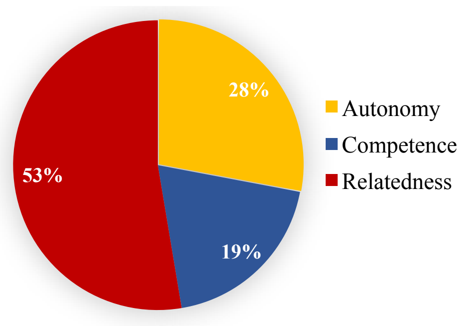
3.2.4 Dataset Statistics



(a) Layer 1: Emotion categories



(b) Layer 1: Need content



(c) Layer 1.1: Need types

Figure 3.2: Corpus statistics for layer 1 and layer 1.1.

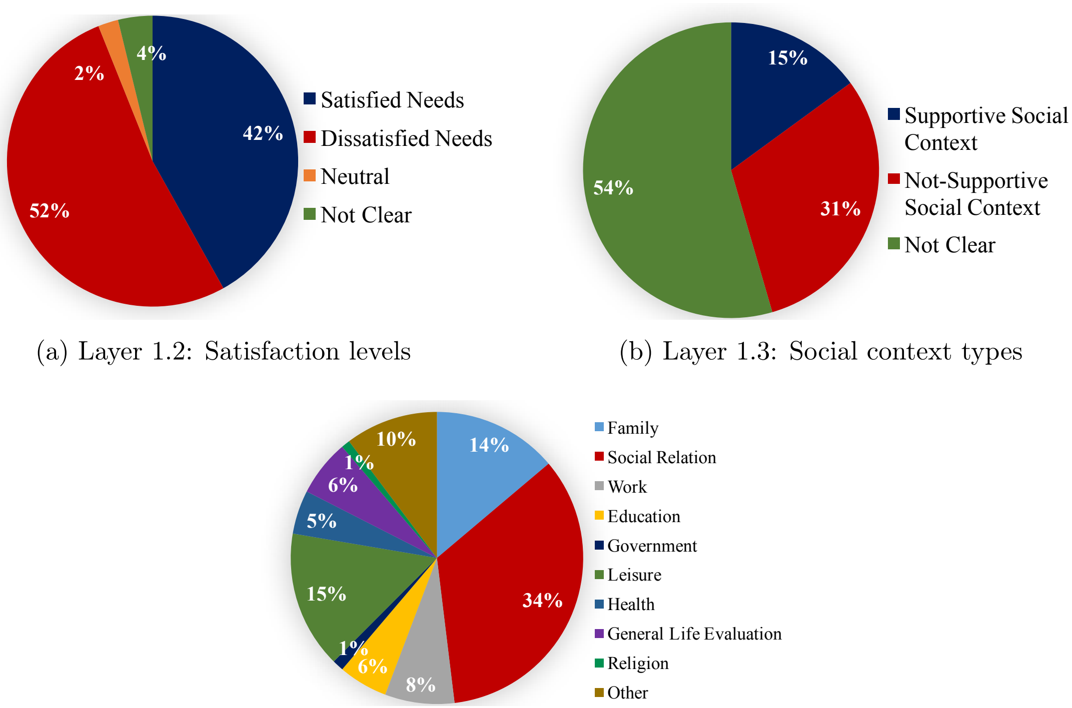
The data analysis in Figure (3.2) charts (a) and (b) show that out of the 18,847 annotated tweets, 66% of tweets that contained emotional tags did not reveal true emotions, such as in the following example:

- "#**Love**, Rosie is the best movie I've ever seen😭😭❤️"

Others did reflect emotions, but there was not enough information to indicate the underlying need, such as in the following tweet:

- "It's actually just not fair that I can't sleep tonight #miserable "
- "#Regret is the worst feeling "

Tweets did reflect emotions or needs are neglected in layer 1, which are around 12513 of tweets. Only 34% of tweets (6334 tweets) that reflect an individual's emotions and convey



(a) Layer 1.2: Satisfaction levels

(b) Layer 1.3: Social context types

(c) Layer 1.4: Life sspects

Figure 3.3: Corpus statistics for layer 1.2, layer1.3 and layer 1.4.

their psychological basic needs are kept, which constructed the Psychological Need Corpus. Upon taking a closer look at the distribution of emotions in the corpus, represented by chart (a) in Figure (3.2), we noticed that the most common emotion category is joy at 41%, followed by sad with 25%. The least frequent emotion is surprise with 1%. Approximately 60.98% of the tweets in the corpus include a single hashtag corresponding to one emotion category, and 38.83% contain multiple hashtags that represent multiple emotion categories or are combined with current events or personal topics. For instance:

- " I wake up every morning and look around like, Is this really my life? #PostCollege #Unsatisfied "
- " Was literally just paid and can't even use my credit card. Thanks to whoever spent my paycheck #frustrated #embarrasing "

For layer 1.1 of the reference model, Figure (3.2) chart (c) shows the distribution based on basic needs types. It can clearly be seen that relatedness is expressed nearly twice as often as the other needs categories, with 52.71%. Autonomy at 27.96% and competence at 19.4% came in second and third, respectively. The most likely explanation of this distribution is that tweets were collected during the occurrence of special events, such as Thanksgiving, Christmas, and New Year's, which is when most social activities happen. The distribution of the satisfaction levels among the tweet data in Figure (3.3) chart (a) shows that the corpus has nearly equal numbers of instances of satisfied 41.7% and dissatisfied 51.9%, while 2.25% of the tweets are neutral. In social context types, as can be seen from Figure (3.3) chart (b), there is an unbalanced distribution between tweets that reflect supportive social context types, which represent 14.8% of the corpus, and tweets that reveal non-supportive social context types, which represent 30.35% of the corpus. Slightly over half of the tweets in the corpus 53.53% lacked enough information for us to identify the type of social context. Figure (3.3) chart (c) summarizes the frequency distribution of the life aspects categories in the corpus. Of the ten life aspect categories, about 34.24% of the corpus consists of tweets related to the social relation aspect, which is considered the most frequent aspect, whereas only 1% of the tweets express basic needs related to the religion aspect.

Chapter 4

Psychological Need Recognition Framework

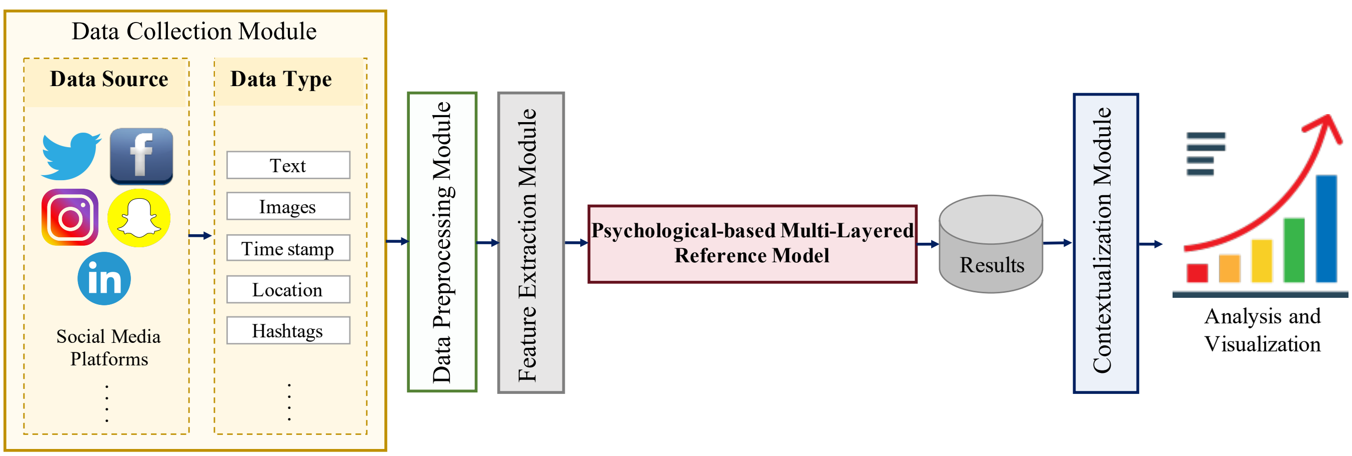


Figure 4.1: An overall flow diagram describing the proposed psychological human need recognition framework.

Figure (4.1) illustrates the proposed psychological need recognition framework. The framework is designed and developed to automatically recognize people psychological needs from social media textual content. It could be utilized in a wide range of applications with diverse contexts. Based on the application objective, in the data collection module, the microblog posts of interest will be gathered using Twitter search API[1]. The microblog posts includes the textual and visual content will be retrieved with its metadata (i.e., post-

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

ing time and geographical location). The multimodal data or, the post interactions data (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 favourite T_f. The textual data will be preprocessed through the Data Preprocessing Module and the features will be extracted using the Features Extraction Module which will be explained in this Chapter. The psychological needs will be recognized automatically using the developed need models that will be explained in details in this Chapter and in Chapter 5. Then, the post interaction data (T_{rt}, T_r and T_f) and metadata (T_l and T_t) will be used by the Contextualization Module before analyzing the results.

4.1 Designing and Developing Psychological Need Models

Figure (4.2) illustrates the learning process to design and develop the psychological need models, namely the Need Content Recognition (NCR) model, the Need Type Identification (NTI) model, the Measuring Need Satisfaction Level (MNS) model, the Social Context Evaluation (SCE) model, and the Life Aspect Identification (LAI) model. For a more comprehensive and deeper analysis, the Frustrated Need Intensity Estimator (FNIE) model and the Satisfied Need Intensity Estimator (SNIE) model are developed to determine the intensity score of the satisfaction level. It explains the datasets used throughout the experiments, the Data Preprocessing Module, the Feature Extraction Module and the features sets explored in each of the reference model's layers, the sampling techniques used to balance the classes' distribution in each layer, the dimensionality reduction step and the machine learning algorithms. All modules and steps are explained below.

4.1.1 Datasets

To ascertain the intensity of the need satisfaction and frustration levels in layer 1.2, we developed two regression models. We used an existing emotion intensity dataset called

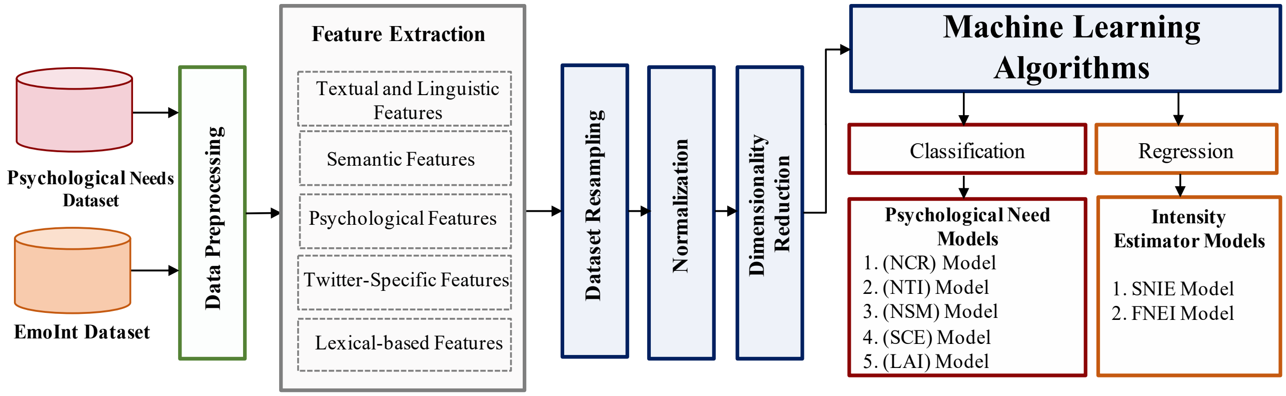


Figure 4.2: An overall flow diagram describing the design and development of psychological need models

EmoInt to train and evaluate our proposed models. EmoInt is a benchmark tweet dataset with affect-related intensity score proposed for WASSA-2017 shared task on emotion intensity [72]. In the construction of the EmoInt dataset, 24 ranking judges manually annotated 7,097 tweets based on four emotion categories: anger, fear, joy, and sadness, along with their associated intensity score range from 0 to 1. Since satisfaction in reference to individual need presents positive emotions and frustration needs lead to negative emotions, we divided the EmoInt dataset into positive and negative emotion datasets. The Negative intensity dataset included 5465 tweets which reflected the emotions anger, fear, and sadness, while the positive intensity dataset encompasses 1608 tweets of a happy and joyful emotion. For each of the datasets, we trained a regression model to determine the intensity score. In layer 1.2, if the tweet was classified to have a satisfied need expression, we applied the Satisfied Need Intensity Estimator Model (SNIE) within the same layer to derive the intensity score of the satisfied need. In the case of tweets classified as frustrated, we used the Frustrated Need Intensity Estimator Model (FNIE) to determine the frustration intensity score.

4.1.2 Data PreProcessing Module

There is no universal or standard method of data preprocessing as it is dependent on the goal of the classification task and the concepts that need to be analyzed. In this thesis, 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 just in the phase of training and testing the need models. 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[2]. The hashtag "#" and the attached words, i.e.,#Love, are considered as one token in order to preserve their meaning. We convert all words into lowercase. Then, we pass all the words through the SnowBall[3] stemming algorithms which stem the words by applying different transformation rules to keep the root forms of the word to be used in textual features. Most of the previous subjective analysis works removed stop words such as pronouns, conjunctions, and/or articles [46]. Stop words are considered to be noisy and not informative due to the high-frequency occurrence. However, in our psychological need classification tasks, personal pronouns could be informative words within layer 1, layer 1.1 and layer 1.3. They can be good indicators of the inner emotional and psychological needs as pointed out in the Non-Violent Communication theory (NVC) Theory [8]. Therefore, and based on preliminary experiments, we kept all the stop words in all layers except layer 1.4 that identifies life aspects. The preprocessing steps of the EmoInt dataset involves removal of the URLs, mentions (@User) and stop words except the negation words. Then words, emojis and punctuation were tokenized using TweetNLP Ark tool. All words converted to lowercase.

4.1.3 Feature Extraction Module

Feature extraction is the process of representing each tweet as a feature vector. Each entry position in a vector corresponds to a feature type extracted from a tweet and represents the weight of that feature. Based on each layer in the reference model, we explore the usage of text-based features, psychological features, contextual features, lexicon-based features and Twitter-specific features as elaborated below. Table (4.3) shows the features used to develop the need model in each layer of the psychological-based multi-layered reference model

Textual and Linguistic Features

- Bag of Words Model (BoW)

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

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 [3]. Given a predefined set of vocabulary V=w_1, w_2,....,w_n, TF-IDF is calculated using equation (4.1).

$$TF - IDF_{w_i} = TF_{(w_i)} \times \log \frac{|D|}{DF_{(w_i)}} \tag{4.1}$$

Where $TF_{(w_i)}$ is the number of occurrence of the word w_i, $|D|$ is the number of tweets in the dataset and $DF_{(w_i)}$ is the number of tweets containing the word w_i. 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 ($n = 2$), trigram ($n = 3$), 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.

- Part of Speech (POS)

POS tagging is the process of tagging a word with its part of speech such as verb, noun, adjective, or adverb based on the detected context. This process has proven to be effective in affects classification. In order to use POS tags as features, we used the CMU ARK Twitter Part-of-Speech Tagger[4]. This POS tagger, developed specifically to be used with social media content (Twitter data), employs 25 tags that consider informal language and Twitter-specific properties [39]. Each token in a tweet is tagged with its POS. We calculated the frequency of each POS tag in a tweet to construct the feature vector. We have 25 different POS tags considered as features.

[4]http://www.cs.cmu.edu/ ark/TweetNLP/

Psychological Features

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

- Linguistic Inquiry and Word Count (LIWC)

We used the LIWC collection of lexicons [104], which were designed and validated based on psychology and cognitive theories. LIWC consists of a set of 92 lexicons and 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. 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 [93] 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 and 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.

Twitter Specific Features

Emojis are text-based visual represention that express emotions. They shave become an important form of communication in online social networks [78]. 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 [110], expressing emotions [90] and revealing aspects of human behavior [29]. 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[5] and create a list with 1519 emojis.

- Sentiment of Emojis

We utilize the emoji sentiment lexicon created by Novak [76] as a feature in layer 1.2 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 [89]. 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 layer 1.1 and the need satisfaction level in layer 1.2. 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

[5] https://emojipedia.org

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 layer 1.1 and the need satisfaction level in layer 1.2.

- 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.

Lexicon-based Features

To measure the satisfaction level in layer 1.2 of the reference model, 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 [8, 25], the emotions expressed signal the state of fulfillment of the needs. Positive and pleasant emotions (i.e. happy, pride, excitement) arise when the need has been met and satisfied, while unmet needs generate negative emotions (i.e. 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 sentiment and emotions lexicons.

- Bing Liu's Opinion Lexicon

The Opinion Lexicon is a manually constructed lexicon from customer reviews about product's features [50]. It consists of 2,006 positive words and 4,781 negative words. For each tweet, we calculate the frequency of each word in the lexicons to form the feature vector.

- Negation Lexicon

Negation words can easily change the sentiment orientation from positive to negative, and in turn, completely reverse the intended meaning of the sentence [81]. Therefore, we used the count of the total occurrence of negated terms (cues or negation signals) such as don't, aren't, neither and never, as features.

- NRC Hashtag Sentiment Lexicon

The NRC Hashtag Sentiment Lexicon[6] is a large, automatically generated lexicon originated using 775,000 tweets that were retrieved using 78 unambiguous and strong positive and negative seeds of hashtags such as #amazing, #good, #excellent, #bad, and #terrible [103]. The lexicon contains 54,129 unigrams (single word), 316,531 bigrams and 308,808 pairs. Each of the words and the phrases are classified with a real-value score between -∞ (most negative) to ∞ (most positive). 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 positive and negative words to form the vector.

- Multi-Perspective Question Answering (MPQA) Lexicon

MPQA[7] is a subjectivity lexicon that identifies subjectivity clues and aspects, including source of opinion, event, and sentiment expressions [28]. It contains a list of over 8000 subjective expressions collected from several resources. The expressions are manually compiled with prior polarities and tagged with their strength. For each tweet we extracted two polarity features: positive words and negative words.

- NRC Word-Emotion Association Lexicon

NRC Word-Emotion Association Lexicon, also known as EmoLex, was constructed manually by conducting a tagging process using the Amazon Mechanical Turk crowdsourcing platform [73]. The Hashtag Emotion Corpus (aka Twitter Emotion Corpus, or TEC) was used to create the lexicon. The lexicon contains 14,182 unigram words tagged with eight emotion categories derived from the Plutchik's wheel of emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust). The words are also tagged with polarity (negative and positive). For each tweet, we extracted 8 features corresponding to the eight emotion category lists. We used EmoLex version 0.92. We also used the Expanded NRC Word-Emotion Association Lexicon, which expands the NRC word emotion association lexicon for the language used in Twitter.

Score-based sentiment and emotion lexicons

We used features derived from several sentiment and emotion-based lexicons. Specifically, we used score-based sentiment and emotion lexicons as features to determine the intensity

[6] https://saifmohammad.com/WebPages/AccessResource.htm
[7] https://mpqa.cs.pitt.edu/

score for satisfied and frustration needs. The intensity score of each employed resource were mapped at the same range from 0 to 1(Transform the lexicons to uniform format). The intensity score of each tweet is calculated by aggregating the intensity scores of each sentiment and emotional token (words and emojis) within the tweet provided by each of lexicons listed in Table (4.1). For any given tweet, each token is reviewed to find a match in the lexicon. If a match is found, then the associated intensity score is retained. All individual intensity scores are compiled in order to calculate the overall score for each lexicon and use them as features. We use a variety of popular and comprehensive lexicons that differ in their data type (general, twitter specific lexicons, emotion based and sentiment-based lexicons), and in their annotation method (manually and automatically annotated lexicons). All the score-based sentiment and emotion lexicons are explained in details below.

- SentiWordNet

The SentiWordNet lexicon[8] is a publicly available synset-based sentiment lexicon introduced by Baccianella et al. [45]. It was constructed based on the WordNet lexical database synset, which is a set of synonyms meant to provide broad coverage. Each of the 115,000+ WordNet synsets is tagged with sentiment information automatically using semi-supervised machine learning method. Each synset is assigned a sentiment score value range between the interval [0.0, 1.0] corresponding to its degree of positivity, negativity or neutrality. We used SentiWordNet version 3.0.

- SentiStrength (SS)

SentiStrength[9] is a lexicon-based method proposed in [6] for use in determining sentiment strength. The lexicon was developed intended for use for short and informal language on any social media platform. It consists of a combination of 2546 booster words, emoticons, negations and intensifiers from LIWC lexicon. The words in the lexicon are annotated manually based on a corpus of 2,600 MySpace comments. Each lexicon entry is assigned a score indicating the polarity and the strength of the sentiment. Two scales are used to evaluate the sentiments. The first ranges from 1 (not positive) to 5 (extremely positive) to indicate the strength of positive sentiment, and, the second, employs -1(not negative) to -5 (overly negative) to indicate the strength of negative sentiment. We used SentiStrength

[8] http://sentiwordnet.isti.cnr.it/

[9] http://sentistrength.wlv.ac.uk/

version 2.0. For each tweet, we extract two types of SentiStrength features: the sum of the positive scores and the sum of the negative scores.

- AFINN

AFINN[10] is a manually constructed lexicon based on Bradley and Lane's Affective Norms for English Words (ANEW) lexicon [75]. ANEW provides emotional ratings for a large number of English words according to the psychological reaction of a person; however, it did not consider the informal words and slang that commonly used in social media platforms. Nielsen in [11] filled that gap by creating the AFINN lexicon, an updated version of the ANEW lexicon, which focuses on microblogging platform language. Over 3,300 English words and phrases were rated based on sentiment strength valence using a numerical sentiment score range from -5 which indicate a very strong Negative Sentiment and +5 for a very strong Positive Sentiment. For each tweet, we calculated the sum of the positive scores and the sum of the negative scores of the tweet words that matched the lexicons words.

- Sentiment140

Sentiment140[11] an automatically generated lexicon from a corpus consisting of a collection of 1.6 million tweets retrieved using these noisy labels: positive and negative emoticons [69]. The lexicon contains words and phrases which include 62,468 unigrams, 677,698 bigrams and 480,010 pair. Each of the listed words and phrases are associated with Real-valued sentiment score between $-\infty$ (most negative) to ∞ (most positive) and 0 for neutral. To ascertain the intensity of a tweet, we extracted two types of features. For each tweet, we add up the positive scores and the negative scores for each word in a tweet, separately.

- NRC Affect Intensity

The NRC Affect Intensity Lexicon[12] consists of 6,000 words annotated with four basic association emotion labels: anger, fear, joy, and sadness [71]. All the words in each emotion category is rated with real value numerical scores, illustrating the intensity strength for that emotion. For instance, "sohappy" is labelled as "joy" emotion, with an intensity score

[10] https://www2.imm.dtu.dk/pubdb/views/publication_details.php?id=6010
[11] http://help.sentiment140.com/for-students/
[12] https://saifmohammad.com/WebPages/AffectIntensity.htm

of 0.86. From the NRC-Affect-Intensity we extracted four features. The individual scores for each word in the tweet matching the four emotion classes are summed.

- SenticNet

SenticNet[13] is a semantic and affective-based lexical resource that provides concept-level sentiment analysis for more than 100,000 natural language concepts [14]. It captures latent information in terms of semantics and sentics. Sentics are the affect information expressed in terms of four affective dimensions (pleasantness, attention, sensitivity, and aptitude). Also, SenticNet provides polarity-based scores between -1 (extreme negative) and +1 (extreme positivity). The intensity score is defined based on the sixteen basic emotions of the well-known Hourglass of Emotions. SenticNet does not rely only on the expressions that explicitly convey emotions by using keyword counts and word co-occurrence frequencies; it is also able to leverage the implicit sentiments by analyzing expressions with semantically related concepts.

- NRC Hashtag Emotion Lexicon

Also known as NRC-Hash-Emo, an automatically created lexicon amassed from tweets with emotion word hashtags, utilizing The Hashtag Emotion Corpus (aka Twitter Emotion Corpus, or TEC) [51]. The corpus was constructed automatically using emotions hashtags such as #happy and #anger. The lexicon contains 16,862 emotion word associations, including eight emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust). Each word in the lexicon is rated with Real-value score between 0 (not associated) to ∞ (maximally associated).

- Life aspects lexicons

Classifying a short text into one of nine life aspect categories can be very challenging, especially when we encounter an unbalanced dataset. External knowledge resources are necessary to help overcome this complication. Relying on lexical resources as external knowledge has proven to be beneficial during short text categorization and word sense disambiguation [62]. We constructed nine life aspect lexicons to help classify the input textual data in the most dominant life aspect. The construction of the nine life aspect lexicons involved the two following steps:

[13] https://sentic.net/

Table 4.1: Score-based intensity lexicons used to determine the need satisfaction and frustration intensity scores

Lexicons	Affective States	Affect Dimension	Annotation Process	Labeling Type	Data Type
AFINN	Sentiment	positive and negative	Manually	Numeric	Twitter
NRC-AffInt	Emotions	anger, fear, sadness and joy	Manually	Numeric	Twitter
NRC-Hash-Emo	Emotions	anger, fear, anticipation, trust, surprise, sadness, joy, and disgust	Automatically	Numeric	Twitter
Sentiment140	Sentiment	positive and negative	Automatically	Numeric	Twitter
SentiStrength	Sentiment	positive and negative	Manually	Numeric	Twitter and MySpace
SentiWordNet	Sentiment	positive, negative and objective	Automatically	Numeric	General
SenticNet	Affects	pleasantness, attention, sensitivity, and aptitude	Automatically	Numeric	General and Social media content

1. Selecting the initial seeds of words

   In order to establish an initial list of words related to each of the nine concepts of life aspects, we referenced online dictionaries and thesauruses. One of such resources, Oxford mini-dictionaries, provides lists of words and phrases categorized based on different subjects and topics. We collected terms listed in each topic category that were relevant to an individual life aspect category. For example the Oxford mini dictionaries related to health domain consist of sub-categories including: "diet", "fitness", "illness", "medicine" and "mental health". Furthermore, each of these sub-categories has their own sub-sub categories. For instance, the "illness" sub-category has the following sub-sub categories: "ailments and diseases", "being ill", "Injuries" and "Recovering from illness". Each of the sub-sub-categories consists of lists of related words and terms such as "recover", "healing" and "well". This collection step was performed for all of the nine life aspects categories: education, family, work, health, government/political, social relation, leisure, religion, and general evaluation. For the general evaluation aspect, we constructed the lexicon using words and phrases that express consistent and constant occurrences.

2. Expanding the words lists

Once the initial list of words was amassed, we moved to the second stage where we extend the list of words in each lexicon by identifying and collecting synonyms and alternative

Table 4.2: Examples of words included in the life aspects lexicons

Life Aspect category	Examples of words included in the lexicons
Work	tasks, occupation, resignation, practicing, agents, executive, company, boss, investment, qualified
Education	learn, diploma, exam, graduate, academic, grade, school, course, GPA, study
Health	anxiety, blood, pressure, workout, painful, drug, surgery, relief, medical, stroke, healthcare
Social life	people, enemy, human, who, relationship, friend, boys, someone, women, guy
Government	prime minster, military, freedom, vote, mayor, poll, reform, campaign, policy, election
Leisure	play, travel, song, paint, game, fun, camp, music, festival, holidays
Religion	church, God, belief, pray, Jesus, buddha, worship, mercy, Christian, Allah
Family	grandma, father, married, spouse, mother, husband, son, boyfriend, girlfriend, sister
General Evaluation	every time, always, forever, until now, almost, constantly, continually, nonstop, 24/7, evermore

expressions. WordNet, a large and well-constructed database, provided a good starting point. WordNet is a lexical database developed at the Cognitive Science Laboratory at Princeton University[14]. WordNet organizes the knowledge in a way that reflects current psycholinguistic theories regarding how humans archive their lexical memories. The information in WordNet is catalogued in logical groupings based on sets of cognitive synonyms called synsets. Each synset consists of a list of synonymous word that are interlinked by means of conceptual semantic similarity relations. Synsets are built with an intrinsic correlation between a concept and its corresponding words which are interchangeable among many contexts. The semantic relations have different types, including: (Is-a/Has-a) relation, (Part-of/Has-part) relation, (Member-of/Has-member) relation and (Substance-of/Has-substance) relation. Figure (4.3) shows a graph from the WordNet visual dictionary[15] to explain (Is-a) relation. Table (4.2) shows examples of words included in each of our life aspect lexicon.

The life aspect features are extracted as described below: First, we count all the text elements in a tweet, including punctuations, numbers, emoji and words. Then, we compare each word in a tweet against all words in the predefined life aspects lexicons. The percentage of each life aspect lexicon is calculated by dividing the number of its word frequency by the total number of the structure elements of the tweet, then multiplying that by 100. Similar

[14]https://wordnet.princeton.edu/
[15]http://wordvis.com/

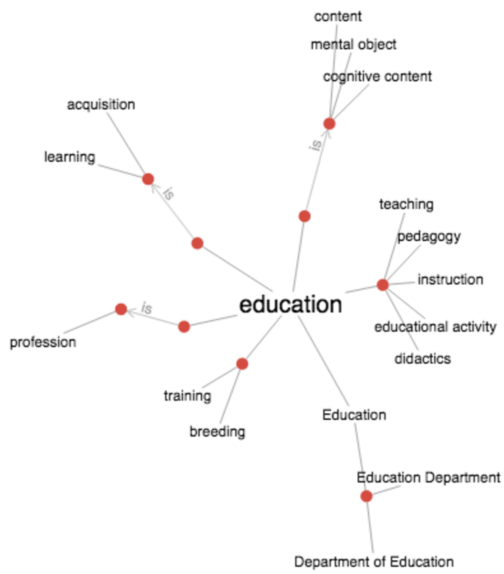


Figure 4.3: A graph from the WordNet visual dictionary showing synonyms of the word "education" using (Is-a) relation.

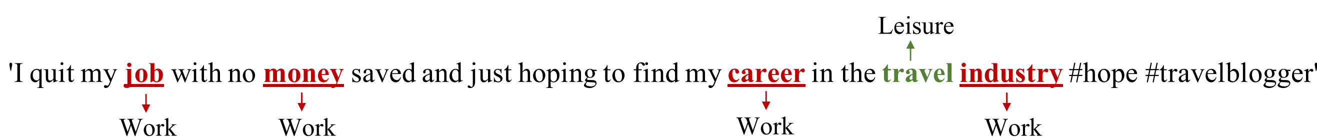


Figure 4.4: Extracting life aspect features from a tweet.

phrases such as (all the time) and (every time) from a general life evaluation lexicon are counted as a single word rather than each separate word. Figure (4.4) explains how life aspect lexical features are extracted. In the example, the tweet has 21 elements. Four words from the work category lexicon compose 19.04% of the tweet, and one word from leisure category lexicon represents 4.761% of the tweet.

Semantic Features

- Emotion Word Embeddings (EWE)

Word embedding is a learning approach used to provide vector representations of a particular word. It captures generic aspects of language structure; namely, semantic and syntactic similarity between words. Words which frequently occur in similar contexts tend to be semantically similar and have similar regions of the vector space. Using word embeddings as features has recently proven to be effective in many text analysis tasks [83], [60] and [100]. Pre-trained word embeddings are utilized when a text analysis task suffers from low resources and a large data set can not be obtained [67]. It is very beneficial to incorporate this type of feature in designing our need models. In addition to capturing the semantic and syntactic context similarity, it is imperative in our need detection framework to preserve the emotional word meaning as well. Therefore, we used the pre-trained Emotion Word Embeddings (EWE) proposed by Agrawal in [1]. EWE is an emotion-enriched word embedding that enhances the regular embedding with respect to emotion analysis. This word embedding captures the affect information in tweets, while other existing generic word embeddings such as Word2vec[16] and GloVe [80] capture only syntactic and semantic information. As mentioned in [1], according to the cosine similarity scores between the word vectors from the most popular pre-trained word embeddings (Glove and Word2vec), the word pair (happy, sad) is more similar than (happy, joy). This example highlights the limitation of using generic word embeddings in emotion-based analysis tasks that require more attention to affect expressions. Agrawal in [1] designed their emotion word embedding using an emotion model firmly grounded in psychology. By incorporating EWE as features, we can capture words with similar emotional meaning such as (happy, joy). The feature vector level within a tweet is calculated by aggregating the embedding values of the words within the tweet using an average word embedding scheme. We ended up with a dimensional vector of 400 for each tweet. Zero values are added for words with no corresponding embedding.

4.1.4 Data Resampling

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 [63]. A number of solutions have been proposed to solve this problem [85]. Based on the nature and the importance of the classification task in each layer of our reference model, we solve the class imbalance problem using one or more of these proper approaches as follows:
In layer 1, 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 (4.4)

[16]https://code.google.com/archive/p/word2vec/

Table 4.3: Features used to develop the need model in each layer of the psychological-based multi-layered reference model.

Features	Layer 1	Layer 1.1	Layer 1.2	Intensity Score	Layer 1.3	Layer 1.4
Textual and Linguistic Features						
• Bag of Words Model (BoW)	x	x	x	x	x	x
• N-gram Language Model (LM)	x	x	x	x	x	x
• Part of Speech (POS)					x	
Psychological Features						
• Linguistic Inquiry and Word Count (LIWC)	x	x	x	x	x	x
• Linguistic Category Model (LCM)		x			x	
Semantic Features						
• Emotion Word Embeddings (EWE)	x				x	
Twitter-Specific Features						
Emojis						
• Emoji Frequency	x	x	x		x	
• Sentiment of Emojis			x	x	x	
• Categories of Emojis		x	x			
• The Color of Emojis		x	x			
Number of Hashtags	x	x				
Lexicons-based Features						
Sentiment Lexicons						
• NRC Hashtag Sentiment			x		x	
• Negation Lexicon					x	
• MPQA					x	
• Bing Liu opinion Lexicon			x		x	
• SentiWordNet				x		
• Sentiment140				x		
• SentiStrength (SS)				x		
• AFINN				x		
• SenticNet				x		
Emotion Lexicons						
• NRC Word-Emotion Association Lexicon (EmoLex)					x	
• NRC Hashtag Emotion Lexicon				x	x	
• NRC Affect Intensity Lexicon				x		
Life Aspect Lexicons						x

shows the class distribution before and after using the under-sampling technique. In layer 1.1, 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) [15]. 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 $\alpha \in [0, 1]$ as equation (4.2) shows and add it to the feature vector. Table (4.5) shows the Recall measure of the minority classes in all layers before and after resampling.

$$x_{new} = x_i + (\bar{x}_i - x_i) * \alpha \tag{4.2}$$

In layer 1.2, 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".

4.1.5 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 explained in equation (4.3), a feature scaling method, after the feature extraction step. 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.

$$x_{sc} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{4.3}$$

Table 4.4: Psychological need data set statistics before and after applying resampling.

Layers	Class name	Resampling technique	Amount of resampling	Before resampling	After resampling
Layer 1	Tweets with need content	-	-	6334	-
	Tweets without need content	Under-sampling	29.50%	12513	8826
Layer 1.1	Relatedness	Under-sampling	36.6%	3333	2111
	Autonomy	SMOTE	19.31%	1771	2113
	Competence	SMOTE	72%	1229	2116
Layer 1.2	Satisfied need	-	-	3295	-
	Dissatisfied need	-	-	2566	-
	Other	SMOTE	662.35%	348	2653
Layer 1.3	Supportive social context	SMOTE	120%	947	2083
	Not supportive social context	-	-	1935	-
	Not clear	Under-sampling	32.73%	3452	2322
Layer 1.4	Work	-	-	487	-
	Education	-	-	345	-
	Health	-	-	307	-
	Family	-	-	876	-
	General evaluation	-	-	396	-
	Government	SMOTE	300%	80	320
	Leisure	-	-	963	-
	Religion	SMOTE	400%	61	305
	Social relation	Under-sampling	42.3%	2196	1266
	Other	-	-	650	-

Table 4.5: Accuracy (A), Precision (P), Recall (R) and F_{score} for some classes before and after applying resampling.

Layers	Befor Sampling				After Sampling			
Layer 1	A	P	R	F	A	P	R	F
Tweet with need content	72.49	0.62	0.44	0.51	69.59	0.65	0.56	0.60
Tweet without need content		0.75	0.86	0.80		0.72	0.78	0.75
Layer 1.1								
Relatedness	69.31	0.78	0.80	0.79	74.81	0.79	0.70	0.75
Competence		0.55	0.47	0.51		0.74	0.83	0.78
Autonomy		0.60	0.64	0.62		0.70	0.70	0.70
Layer 1.3								
Supportive social context	60.0	0.44	0.34	0.39	68.87	0.78	0.87	0.82
Non-supportive social context		0.55	0.57	0.56		0.64	0.64	0.64
Not clear		0.65	0.68	0.67		0.63	0.56	0.59

4.1.6 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 [44], we consider the use of the Gain Ratio (GR) [52], 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 equation (4.4):

$$IG(x) = H(D) - \sum_{j} \frac{|D_j|}{|D|} H(D_j) \tag{4.4}$$

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 equation (4.5):

$$H(D) = \sum_{i \in Y} P(i) log P(i) \tag{4.5}$$

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 using equation (4.6):

$$GR(x) = \frac{IG(x)}{IV(x)} \tag{4.6}$$

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 Chapter 5.

4.1.7 Machine Learning Algorithms

In constructing our framework models, we explored the most well-known machine learning algorithms, which we selected based on their different learning methods and techniques. Due to the lack of an existing psychological need dataset, in this work we constructed a high-quality annotated dataset rather than a large dataset, which made adopting conventional machine learning algorithms preferable to deep learning algorithms, as the latter are powered by massive amounts of data. For classification tasks, We selected the Multinomial Naive Bayes algorithm (MNB) as a probabilistic classifier, the Support Vector Machine algorithm (SVM) as a linear-decision boundary algorithm, the Logistic Regression (LR) as a regression classifier, the Random Forest algorithm (RF) as an ensemble classifier, the K-Nearest Neighbors algorithm (K-NN) as an instance-based algorithm, and the Decision Tree algorithm (DT) as a rule based classifier. For regression tasks, we used the Support Vector Regression (SVR) algorithm. Brief descriptions of these algorithms and their learning techniques are provided below.

- Support Vector Machine (SVM)

Support Vector Machine (SVM) is a discriminative, non-probabilistic machine learning algorithm that is considered to be one of the most common learning methods [113]. SVM has proven to be more robust and effective on high dimensional feature space (i.e. textual data). The basic idea behind the Support Vector Machine algorithm is to determine the optimal hyper-plane in n-dimensional space that distinctly segregates the different classes. It solves an optimization problem by finding the values for the coefficients that maximizes the distance between the hyperplane and the closest data points of both classes. This distance is called margin and the closest points are called support vectors. They define the position of the hyperplane to construct the classifier. Linear support vector machine adopts the linear equation (4.7):

$$f(x) = w^T x_i + b \tag{4.7}$$

Where w is the weight of the vector, x is feature vector and b is the bias. To find the optimal separating hyper-plane, the following optimization function need to be solved:

$$max_w \frac{2}{\|w\|} \ subject \ to \ w^T x_i + b \begin{cases} \geq 1 & if \ y_i = +1 \\ \leq -1 & if \ y_i = -1 \end{cases} for \ i = 1 \dots N$$

We have used a linear SVM algorithm. We adopt the Least Square Errors (LSE) SVM and an L2-regularized L2-loss implemented in *LIBLINEAR4* library [35]. For the reference model layers with multi-class classification tasks, we use a multi-class support vector machine by integrating an ensemble approach called *one-versus-all (OVA)*. Given m classes, OVA strategy builds different binary classifiers, one for each class. For the j_{th} classifier, training data belong to this class will be the positive instances and all the other instances will be negative instances. To classify new instances x, classifiers vote and the class with the most votes is assigned to x.

We used Support Vector Regression (SVR) to solve the regression problem in determining the satisfied and the frustrated intensity scores [35]. SVR performs linear regression using epsilon insensitive loss function. The optimization problem can be formulated as the following equation (4.8):

$$minimize \ \frac{1}{2}\|w\|^2 \ subject \ to \ \begin{cases} y_i - \langle w, x_i \rangle \ - b \leq \varepsilon \\ \langle w, x_i \rangle \ + b \ - y_i \leq \varepsilon \end{cases} \tag{4.8}$$

Where ε is the specified deviation tolerated. Two slack variables are used to cope with infeasible constraints. The optimization problem can be redefined as equation (4.9):

$$minimize\ \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*)\ subject\ to \begin{cases} y_i - \langle w, x_i \rangle\ - b \le \varepsilon + \xi_i \\ \langle w, x_i \rangle\ + b\ - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \tag{4.9}$$

- Logistic Regression

Logistic regression is a statistical method that measures the relationship between the categorical dependent variable and independent variables [61]. It is much more robust in correlated features than the Naïve Bays algorithm.The model is learned as a liner regression; it takes linear combinations of features and predicts the values for the coefficients that weight each input variable. The predicted values (probability predictions) are transformed using a non-linear function called logistic function or sigmoid function to estimate the probabilities of the output class. The function maps the predicted real numeric values into a binary value [0,1].

Liner regression for continuous outcome is modeled as a linear combination of the features:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots\ldots. + \beta_n x_n$$

Logit Function or Sigmoid Function in equation (4.10):

$$\sigma(x) = \frac{1}{1 + e^- x} \tag{4.10}$$

Where: β_0 is the intercept, X=x_1, $x_2 \ldots . x_n$ are independent variables, β=β_1,$\beta_2 \ldots \beta_n$ are the coefficient of respective features, and e is base of natural log.

- Decision Trees

Decision Tree (DT) is a non-parametric machine learning algorithm that uses a rule-based approach for classifications [84]. It represents data in a form of tree structures where nodes represent features, branches represent conjunctions of features values, and leaves represent class labels. The paths from root node to leaf represent the classification rules, which is in the form of if-then-else conditions. DT classifier is constructed through a step

by step incremental process as follows:
The training data is partitioned hierarchically to smaller subsets based on split conditions over features. The features that can effectively split the training data into subsets are selected to build each root node of the tree. The splitting criterion is derived from calculating Entropy and Information Gain values. The features with high information gain values build each root node of the tree. The process continues a recursive strategy for the partitioned subsets. The final result is a tree structure with decision nodes and leaf nodes. DT is slow and can be subject to over-fitting; however, it is simple, easy to interpret, robust to outliers and can handle heavy skewed data effectively. A pruning technique is used to avoid overfitting data. We used C4.5, a univariate decision tree algorithm with pruning confidence threshold C=0.25, developed by Ross Quinlan.

- Naïve Bayes

Naïve Bayes is a statistical machine learning algorithm that utilizes a probabilistic approach based on Bayes' theorem [66]. It assumes that all features are important, yet unrelated and independent from each other (independently contribute to the probability). In other words, the presence of a particular feature in a class is unrelated to the presence of any other feature. This assumption of conditional independency simplifies the calculation and yields superior performance in text classification. It is uncomplicated, fast and can be used effectively with a small amount of training dataset. Despite its simplicity, it is a surprisingly powerful algorithm, and has been known to outperform other more sophisticated classification algorithms. NB classifiers are associated with two types of probabilities: prior probability and posterior probability. Prior probability is the probability of each class which is independent of any information. The posterior probability is the conditional probability for each class given value of feature x.

The Naive Bayes classifier assumes that the effect of the value of feature x_j on a given class c_i is independent of the values of other features. Let D be a training dataset, X represent the vector with n features $X = x_1, x_2, \ldots .x_n$ and suppose there are m classes $Y = y_1, y_2, \ldots ..y_m$. The posterior probability $P(y_i|x)$ that x belongs to y_i can be calculated from the equation (4.11) where $P(y_i)$ is the class prior probability, $P(x)$ is the predictor prior probability and $P(x|y_i)$ is likelihood (the probability of predictor given class y_i).

$$P(y_i|x) = \frac{P(x|y_i)P(y_i)}{P(x)} \tag{4.11}$$

$$= \frac{p(y_i)\prod_{j=1}^{|x|} P(x_j|y_i)}{p(x)}$$

P(x) is constant that take the same value for all classes, so it can be ignored as in equation (4.12). The class with highest probability is selected at the end.

$$P(y_i|x) \propto p(y_i)\prod_{j=1}^{|x|} P(x_j|y_i) \tag{4.12}$$

- Random Forest

Ensemble is a learning technique that combines multiple classifiers with weak and unstable performance into one ensemble classifier [12]. The aim is to develop a powerful ensemble classifier with more accurate predictions that outperform the generalization ability of the individual classifiers on their own. Probably the most well-known algorithm that applies this bagging technique is Random Forest (RF). RF uses an ensemble learning method with DT as an inner base model for classification. It combines individual uncorrelated fully-grown DT classifiers that operate as an ensemble in order to prevent overfitting. The prediction result is an ensemble classifier made up of all the combined DT classifiers. The class label is selected based on the majority votes (bagging aggregation). An ensemble classifier H For the training dataset D, with N as ensemble size is constructed as follows: It creates random samples S_i from the training data set D with replacement using bootstrap method.

$$S_i = BootstapSample(D)$$

Then trains multiple decision trees h_i classifiers on each of the independent bootstrapped samples S_i independently to improve the generalization ability of the model as explained in constructing DT classifier.

$$h_i = learn(S_i)$$

Add classifier to ensemble $H = H \cup h_i$, ensemble classifier $H : H{=}h_1\ ,h_2,\ldots h_n$. Then all component classifiers vote for which of the k classes in C should be assigned to unlabeled observation x. Obtain votes for all classes as follows:

$$V_y = \sum_{i-1}^{N} v_i, y \; for \; y = 1, \ldots .C$$

Then select class with the majority voting. The class that receives most votes will be assigned to x as final prediction.

- K-Nearest Neighbor (K-NN)

K-Nearest Neighbor (K-NN) is non-parametric, instance-based classification algorithm [2]. Unlike the previously presented classifiers, K-NN does not construct an explicit model. There is no training phase; it simply stores the features space of all training instances, and uses it directly as "knowledge" for the prediction phase. K-NN memorizes training instances and leaves all the classification work to the end. Consequently, it is referred to a lazy learner, or, a memory-based learner. The K-NN algorithm is simple and has been widely applied to text categorization; however, it requires lot of memory and expensive computation. In the prediction phase, K-NN goes through all the instances of training data and calculates the distance between them and the new instance. The distance between two instances is calculated using a commonly used similarity measure called Euclidean distance. It then stores and ranks all the training instances based on this distance. After selecting the nearest neighbors, it searches the entire stored training instances (feature vectors) to retrieve the closest instances. The Predictions are made by a majority vote of its neighbors.

To classify new instance x, select the number of the closest neighbors k. For all instances in the training dataset D:
Compute the distance between the new instance and the training instances $X(x_i,\grave{x}_i)$ using Euclidean equation (4.13):

$$X(x_i, \grave{x}_i) = |x_i, \grave{x}_i| = \sqrt{\sum_{i=1}^{d} (x_i, \grave{x}_i)^2} \tag{4.13}$$

The distance is stored in ascending order with the index of the training instance. Then the K nearest neighbors need to be selected from the sorted collection. To predict the class for new instance, it gets the labels of the selected K entries to apply the majority voting (the class with the highest frequency). Usually, the optimal value of k is empirically determined. We are running the K-NN algorithm several times with different values of K. The K value with high accuracy and low error rate is selected.

Chapter 5

Experiments and Evaluation

We experimentally evaluate the performance of our proposed need recognition models on the psychological need dataset and the EmoInt dataset. The experiments are designed with the goal of measuring the effectiveness of the five classification models of our framework: NCR, NTI, NSM, SCE and LAI models and the two intensity estimator regression models: FNIE and SNIE. Since we are reporting the result of baseline, a set of experiments were conducted to validate the importance of different textual features, semantic features, psychological features and Twitter-specific features along with different machine learning algorithms. The experimental settings, evaluation metrics and results are described below.

5.1 Experimental Setting

The psychological human need dataset was divided into 70% for training, and 30% for testing, while preserving the class distribution. For the classification algorithms, as we mentioned we explored the most well-known machine learning algorithms, which we singled out based on their various learning methods and techniques, in order to provide benchmark results. For the regression problem, we split each of the positive and the negative intensity datasets into 70% for training and 30% for testing. We used the machine learning algorithm libraries implemented in *Weka*. *Weka* stands for *Waikato Environment for Knowledge Analysis*; a machine learning software developed at the University of Waikato [47]. While conducting the experiments, we followed an incremental feature selection approach. We comparatively evaluated the predictive power of each distinct feature and reported the obtained result before and after any feature addition, both as a set and individually.

5.2 Evaluation Metrics

The classification models' performance is assessed using the metrics of Recall (R), Precision (P), F_{score} and Accuracy (A). Accuracy is defined as shown in equation (5.1) and F_{score} is calculated as illustrated in equation (5.2).

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \tag{5.1}$$

Where True Positives (TP) is the outcome where the model predicted a positive class and the actual output was also positive. True Negatives (TN) is the outcome where the model predicted a negative class and the actual output was also negative. False Positives (FP) is the outcome where the model predicted a positive class and the actual output was negative. False Negatives (FN) is the outcome where the model predicted a negative class and the actual output was positive.

$$F_{score} = 2 * \frac{P * R}{P + R} \tag{5.2}$$

Recall is calculated using equation (5.3)

$$Recall = \frac{TP}{TP + FN} \tag{5.3}$$

Precision is calculated using equation (5.4)

$$Precision = \frac{TP}{TP + FP} \tag{5.4}$$

The regression models are evaluated using the Pearson Correlation Coefficient (r) , equation (5.5) of model predictions with the EmoInt gold ratings and the Root Mean Squared Error (RMSE) explained in equation (5.6) .

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{5.5}$$

Where $\bar{x}$=mean of x and $\bar{y}$=mean of y.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y_i} - y_i)^2}{n}} \tag{5.6}$$

Where $\hat{y_i}$ is the predicted value, y_i is the actual value and n is the number of observations.

5.3 Experimental Results

5.3.1 The Effectiveness of the Need Content Recognition (NCR) Model

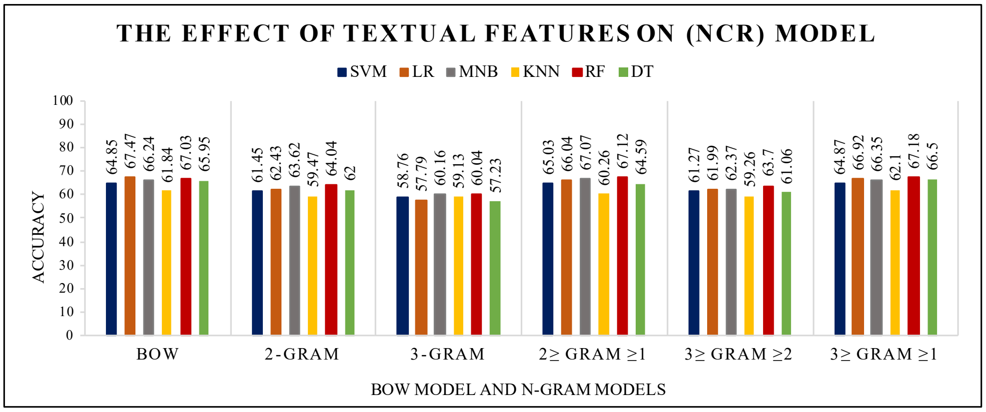


Figure 5.1: The effect of different textual features on the accuracy of the NCR model.

We first study the impact of the different textual features BoW and n-gram models, including unigrams, bigrams and trigrams, on the model's performance. We consider how they interact both individually and in combination.The graphical comparison in Figure (5.1) illustrates these interactions. As we can see from the graph, using unigrams and the combination of all the unigrams, bigrams and trigrams, yields the best performance in comparison to the use of bigram and trigram models.The combination of the unigrams, bigrams and trigrams provides slightly better results when used for the following classifiers: SVM with an accuracy of 64.88%, K-NN (62.1%), RF with (67.18%) and DT shows 66.5% accuracy. Next, we investigate the impact of the LIWC psychological lexicon, emojis and the number of hashtag features on the models' performance. Table (5.1) shows the accuracy and F_{score} for all the selected machine learning algorithms, using all the of features both as a set and individually. Table (5.1) shows, we notice that using the LIWC psychological lexicon alone has a positive influence on the need content recognition model for all classifiers. In addition, considering the frequency of use of emoji seems to provide a slight advantage to all the models. There are no significant changes in the model accuracies after combining the LIWC lexicon with the frequency of Emoji and the number of hashtags features. Combining the LIWC lexicon, the frequency of Emoji, the number of hashtags and the n-gram model have improved the accuracy significantly for MNB classifier by (11.78%) and slightly for LR classifier by (4.87%), K-NN by (3.56%) and DT by (1.64%) and no change in RF accuracy. SVM classifier achieved an accuracy of 64.81%,

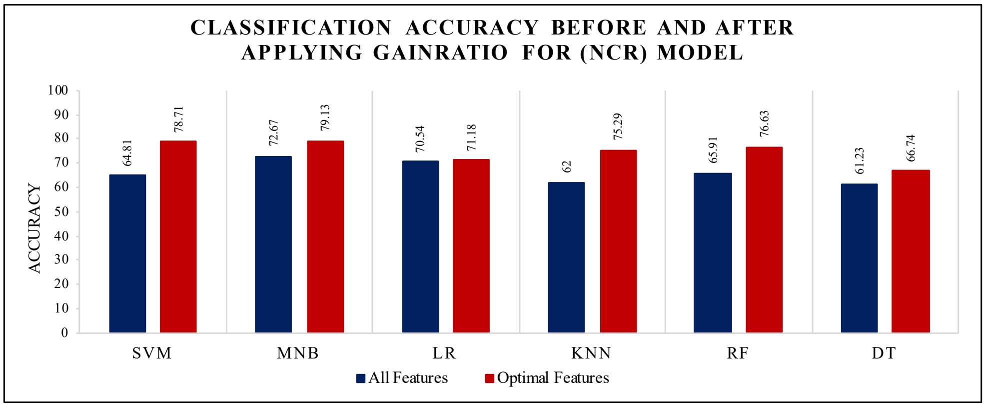


Figure 5.2: NCR model accuracy before and after selecting the most predictive features using GainRatio.

Table 5.1: Accuracy and F_{score} of the NCR model, comparing the use of different features.

	SVM		MNB		LR		K-NN		RF		DT	
Features	A	F	A	F	A	F	A	F	A	F	A	F
LIWC	67.05	0.65	60.83	0.51	65.94	0.64	58.44	0.58	65.69	0.64	59.45	0.59
Emotion Word Embeddings (EWE)	66.74	0.65	58.91	0.54	66.31	0.65	59.61	0.59	64.39	0.61	57.26	0.57
LIWC + Emojis	67.09	0.66	60.91	0.52	65.94	0.64	58.66	0.58	66.29	0.64	59.55	0.59
LIWC + Emoji+ Hashtag Numbers	66.35	0.652	60.89	0.52	65.67	0.64	58.44	0.58	65.67	0.64	59.59	0.59
LIWC + Emoji + Hashtag Numbers + Emotion Word Embeddings (EWE)	68.72	0.68	61.95	0.59	68.74	0.67	60.77	0.60	65.11	0.62	59.92	0.59
LIWC +3≥gram≥1+ Emoji + Hashtag Numbers	64.81	0.68	72.67	0.72	70.54	0.70	62.00	0.61	65.91	0.63	61.23	0.61

which is lower when compared with the 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. Out of the 24,013 features, we examine the most predictive features using different threshold values (0.01, 0.05 and 0.09). Using a threshold value of 0.01 leaves us with 2526 features, and improved the accuracy for SVM by 13.9%, RL by 0.64%, and DT by 5.51%. Using 0.05 threshold value resulted in 2106 features and boosted the accuracy by 6.32% for MNB, 13.29% for K-NN and 10.72% for RF, as shown in Figure (5.2). The MNB classifier achieved the best accuracy in recognizing need content with at 79.13%, with a 0.77 F_{score}, as Table (5.8) shows.

5.3.2 The Effectiveness of the Need Type Identification (NTI) Model

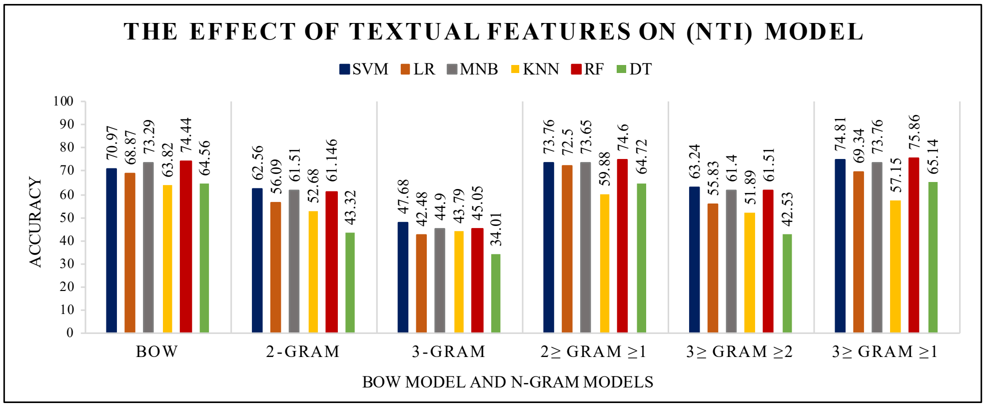


Figure 5.3: The effect of different textual features on the accuracies of the NTI model.

Table 5.2: Accuracy and F_{score} of the NTI model, comparing the use of different features.

	SVM		MNB		LR		K-NN		RF		DT	
Features	A	F	A	F	A	F	A	F	A	F	A	F
LIWC	68.28	0.68	63.30	0.63	68.34	0.68	67.08	0.66	71.76	0.71	60.35	0.60
LIWC + LCM (DAVs, IAV, SV)	68.82	0.68	63.40	0.632	68.98	0.68	66.82	0.65	72.34	0.720	60.51	0.60
LIWC + Emojis	68.66	0.67	63.09	0.629	68.61	0.68	66.92	0.65	72.39	0.72	59.77	0.59
LIWC + Emoji + LCM (DAVs, IAV, SV)	68.76	0.682	63.30	0.63	69.08	0.69	67.19	0.66	73.02	0.72	60.30	0.60
LIWC + Emoji + LCM (DAVs, IAV, SV) + Hashtag Numbers	69.24	0.69	63.51	0.63	69.13	0.69	66.92	0.65	72.45	0.72	59.56	0.59
LIWC + Emoji + LCM (DAVs, IAV, SV) + Hashtag Number + Categorized Emoji	69.40	0.69	63.35	0.63	68.92	0.68	66.08	0.65	73.55	0.73	59.56	0.59
LIWC + Emoji + LCM (DAVs, IAV, SV) + Hashtag Number + Categorized Emoji + Colored Emoji	70.03	0.70	63.03	0.62	68.71	0.68	65.98	0.65	72.45	0.72	59.41	0.59
LIWC + 3≥gram≥1 + Emoji + LCM (DAVs, IAV, SV) + Hashtag Number + Categorized Emoji + Colored Emoji	79.91	0.79	76.34	0.76	72.92	0.73	70.82	0.70	77.65	0.77	66.50	0.66

The experiment results with textual features show that the combination of the unigrams, bigrams and trigrams achieved better results for SVM, MNB and RF classifiers, as depicted in Figure (5.3). Using only the unigram feature provides the best accuracy for K-NN and DT, while the combination of unigrams and bigrams are best for RF classifier. In Table (5.2), the outcomes of using the other features are listed. All the classifiers achieved acceptable ranges of accuracies after applying the psychological features derived from the LIWC and LCM lexicons (DAVs, IAV, SV). This is achieved because LIWC lexicon has different psychological dimensions that can be directly linked to each need types. The ad-

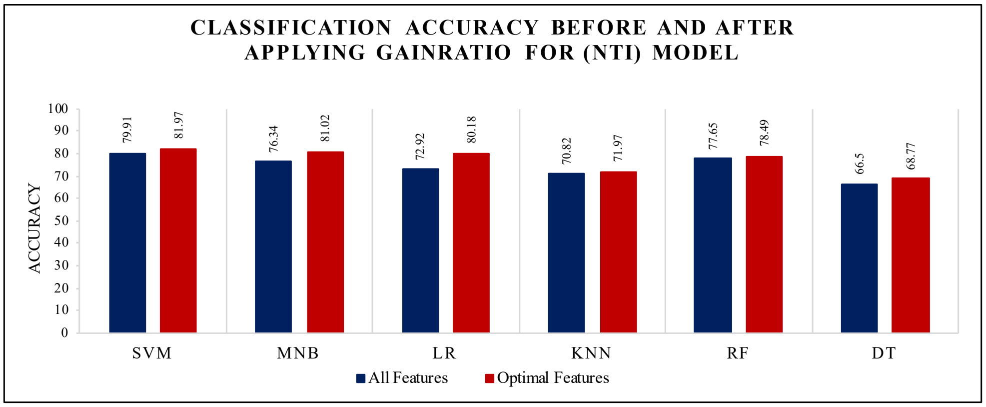


Figure 5.4: NTI model accuracy before and after selecting the most predictive features using GainRatio.

dition of the number of hashtag features and the frequency of emoji has slightly increased the accuracy for SVM and RF. Using all the emoji features, including the frequency of emoji, the categorized emoji and the colored emoji has not improved the accuracies except for a slight increase within the SVM classifier. The combination of all the features results in the maximum accuracy for all the classifiers, especially for MNB classifier, with an absolute accuracy gain of 13.31%. After using GainRatio to select the best features out of all 9500 features for each classifier with different threshold values, the accuracy increases marginally, as shown in Table (5.8) and Figure (5.4). The best classifier in identifying need type is SVM, showing an accuracy rate of 81.97% and a 0.81 F_{score}.

5.3.3 The Effectiveness of the Need Satisfaction Level Measurement (NSM) Model

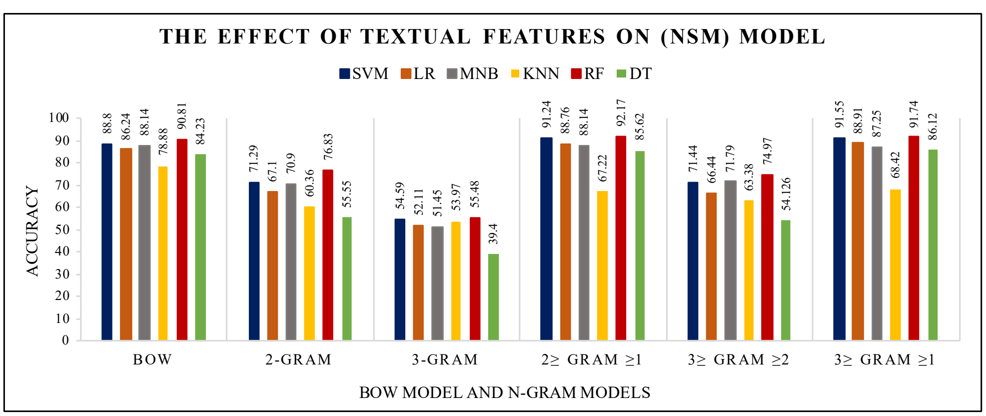


Figure 5.5: The effect of different textual features on the accuracies of the NSM model.

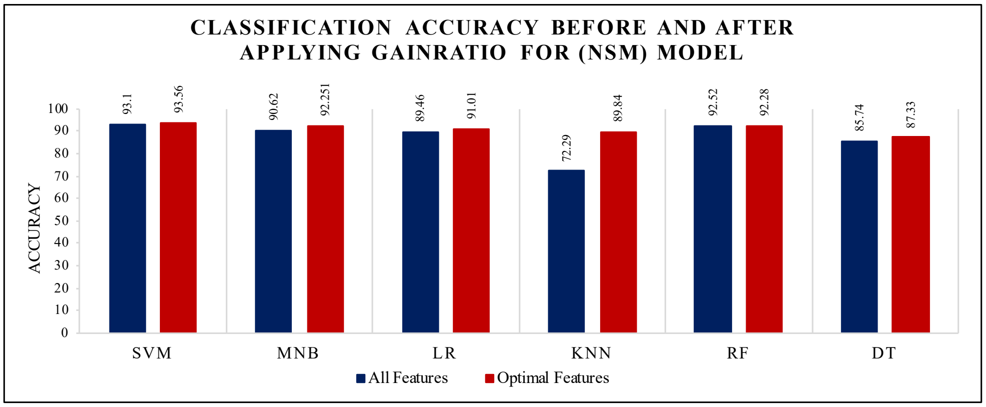


Figure 5.6: NSM model accuracy before and after selecting the most predictive features using GainRatio.

Table 5.3: Accuracy and F_{score} of the NSM Model, comparing the use of different features.

	SVM		MNB		LR		K-NN		RF		DT	
Features	A	F	A	F	A	F	A	F	A	F	A	F
LIWC	72.10	0.71	65.40	0.63	72.87	0.72	75.31	0.75	89.65	0.89	80.70	0.80
LIWC + Emojis	71.21	0.70	65.36	0.63	72.99	0.728	75.125	0.74	89.57	0.89	80.70	0.80
LIWC + Emojis + Sentiment Emojiss	71.98	0.71	65.90	0.63	73.42	0.73	74.89	0.74	90.15	0.90	82.48	0.82
LIWC + Emojis + Sentiment Emojiss + Categorized emoji	72.26	0.72	66.21	0.64	73.49	0.73	74.97	0.74	90.31	0.90	83.10	0.83
LIWC + Emojis + Sentiment Emojiss + Categorized Emoji + Colored Emoji	72.41	0.71	66.05	0.64	73.45	0.73	75.04	0.74	90.43	0.90	83.22	0.83
LIWC + NRC Hashtag Sentiment + Opinion Lexicons	71.52	0.71	65.71	0.63	73.11	0.72	75.28	0.75	90.12	0.90	81.05	0.81
LIWC + NRC Hashtag Sentiment + Opinion Lexicons + Emojis + Sentiment Emojiss + Categorized Emoji + Colored Emoji	72.57	0.72	65.86	0.63	73.76	0.73	74.93	0.74	90.04	0.90	82.87	0.82
LIWC + 3≥gram≥1 + NRC Hashtag Sentiment + Opinion Lexicons + Emojis + Sentiment Emojiss + Categorized Emoji + Colored Emoji	93.10	0.93	90.62	0.90	89.46	0.89	72.29	0.71	92.52	0.92	85.74	0.85

Based on the comparison graph for BoW and n-gram models in Figure (5.5), the highest accuracy was achieved by SVM, LR and DT classifiers when combining unigrams, bigrams and trigrams; whereas, when combining unigram and bigrams MNB and RF achieved the best accuracies. K-NN classifier responded best when using the unigram model alone. As illustrated in Table (5.3) , the RF and DT models performed very well and exhibited high accuracy rates when applying the LIWC psychological lexicon. Since LIWC lexicon has dimension for *Affective Processes* with many sentiment (positive and negative) and emotion categories (anxiety, anger and sadness), this could lead the increased in the performance. Adding emoji features, including the frequency of emoji, the sentiment, the categorized, and the colored emojis increases the accuracy slightly, with the exception of the K-NN classifier. While adding the NRC and the opinion Sentiment Lexicons did not significantly affect the accuracy on most models, there was a slight rise (2.17%) in accuracy for the DT classifier. A markedly high performance is produced for all the classifiers except K-NN when combining all the features, especially the SVM classifier, which achieved 93.10% the heist accuracy. The K-NN classifier archived its best result using the LIWC psychological features alone, effectuating an accuracy of 75.31%. In the feature selection technique, applying the most predictive features with a threshold of 0.01 gives the highest accuracy of 92.25% when used for MNB, and 91% for LR, as shown in Table (4.4) and Figure (5.6). A threshold of 0.05 gives the best result for SVM classifiers, showing 93.56% accuracy, and also for RF (92.28% accuracy). For K-NN classifier, eliminating the features with a 0.09 threshold value increased the accuracy to its best (89.84%). Among all of the evaluated machine learning algorithms, SVM is the best in determining the need satisfaction level, Table (5.8) .

The Effectiveness of the Intensity Estimator Models

Results show that using the combination of unigram and bigram models as well as the combination of all the n-gram models provides good outcomes $r(0.62)$ for SNIE and $r(0.61)$ for FNIE) and tend to be more predictive than the other models as Figure (5.7) shows. As illustrated in Table (5.5) and Table (5.6) , using the LIWC lexicon lead to an average r of (0.58) for the SNIE model, and (0.51) for FNIE model, suggesting that the psychological l features are effective for intensity determination. Adding the NRC Affect Intensity Lexicon led to a slight increase in r score for both models. Applying SentStrangth does not have a significant impact on the SNIE model; however, it did improve the performance of the FNIE model. Using the AFNN lexicon has the opposite effect, where a slight improvement was noted in the SNIE model's performance, but not for the FNIE model. The experiments also determined that there is improvement for both models when using S140 lexicon and Sentiment Emojiss features. The addition of the Hashtag Sentiment Lexicon and the SentiWordNet lexicon did not positively affect the model performance due to the presence of redundant features in the lexicons. Among all the lexicons utilized, LIWC is the most predictive single lexicon. Combining all the score-based sentiment and emotion lexicons with the textual features produces a statistically significant improvement and has boosted the correlation r from (0.64) to (0.71) for SNIE and for FNIE from (0.59) to (0.68). The RMSE for both models are reduced from (0.158) to (0.14) for SNIE model and from (0.15) to (0.13) for the FNIE model.

A noticeable improvement is also obtained after applying the GainRatio, which increases r values from (0.71) to (0.73) for SNIE model and (0.68) to (0.72) for FNIE model

Table 5.4: Pearson correlation r and RMSE for the final FNIE and SNIE models.

Intensity estimator models	Regression model	Pearson correlation r	RMSE
Satisfied Need Intensity Estimator (SNIE) Model	SVR	0.73	0.14
Frustrated Need Intensity Estimator (FNIE) Model	SVR	0.72	0.13

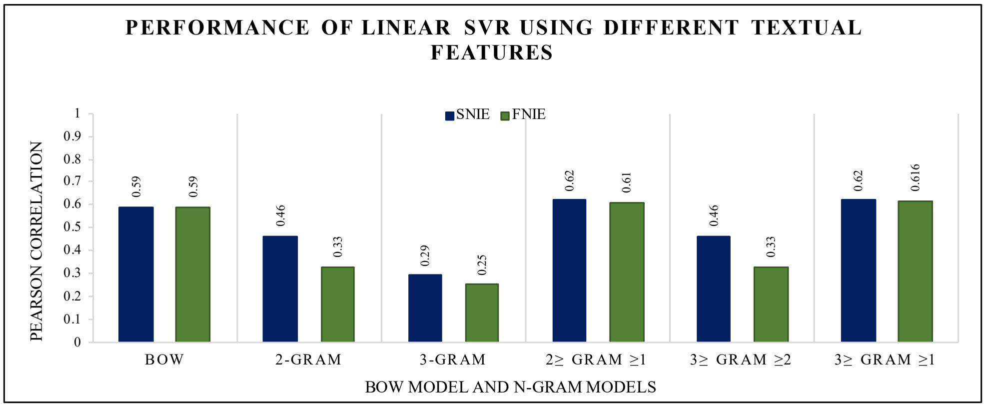


Figure 5.7: The effect of different textual features on the accuracy of the SNIE and FNIE models.

as Table (5.4) and Figure (5.8) show.

5.3.4 The Effectiveness of the Social Context Evaluation (SCE) Model

As Figure (5.9) shows, after comparatively evaluating the predictive power of the BOW model and the n-gram models, the combination of the unigram, bigram and trigram is selected because it provides the best results for most of the classifiers. As demonstrated in Table (5.7), using LIWC and LCM (DAVs, IAV, SV) psychological features also result in decent outcomes for all the classifiers. RF achieved the highest accuracy with 71.45%, and lowest was DT at 60.41%. Using the pre-trained emotion embeddings ended up with acceptable results for some classifiers, including SVM (65.45%), RF (65.82%), LR(64.87%) and K-NN(59.83%), while a lesser performance was noted for the MNB(48.63%) and DT(49.36%) classifiers. Using sentiment-based lexicon features showed satisfactory results among most of the classifiers; however, all the classifiers, except DT, achieved better accuracy when using emotion-based lexicon features. Specifying the emotion categories such as "disappointment" "anticipation" and 'Trust' helped to determine the surrounding social context type. For all classifiers, combining the psychological feature LIWC with emotion-based lexicon features enhanced the accuracy more than when these features are utilized individ-

Table 5.5: SNIE model performance, comparing the use of different features.

Features	Pearson Correlation r	RMSE
LIWC	0.58	0.17
NRC-Hash-Emo + SentiStrength	0.59	0.165
LIWC + NRC Affect Intensity	0.59	0.165
LIWC + NRC Affect Intensity+ SentiStrength	0.599	0.165
LIWC + NRC Affect Intensity + SentiStrength + AFINN	0.60	0.164
LIWC + NRC Affect Intensity + SentiStrength + AFINN + Sentiment140	0.62	0.16
LIWC + NRC Affect Intensity + SentiStrength + AFINN + Sentiment140 + NRC-Hash-Emo	0.627	0.16
LIWC + NRC Affect Intensity + SentiStrength + AFINN + Sentiment140 + NRC-Hash-Emo + SentiWordNet	0.625	0.16
LIWC + NRC Affect Intensity + SentiStrength + AFINN + Sentiment140 + NRC-Hash-Emo + SenticNet + SentiWordNet + Sentiment Emojis	0.641	0.158
LIWC + NRC Affect Intensity + SentiStrength + AFINN + Sentiment140 + NRC-Hash-Emo + SenticNet + SentiWordNet + Sentiment Emojis + 3≥gram≥1	0.71	0.14

Table 5.6: FNIE model performance, comparing the use of different features.

Features	Pearson Correlation r	RMSE
LIWC	0.51	0.16
NRC-Hash-Emo + SentiStrength	0.43	0.16
LIWC + NRC Affect Intensity	0.52	0.16
LIWC + NRC Affect Intensity + SentiStrength	0.54	0.15
LIWC + NRC Affect Intensity + SentiStrength + AFINN	0.54	0.15
LIWC + NRC Affect Intensity + SentiStrength + AFINN + Sentiment140	0.57	0.15
LIWC + NRC Affect Intensity + SentiStrength + AFINN + Sentiment140 + NRC-Hash-Emo	0.58	0.15
LIWC + NRC Affect Intensity + SentiStrength + AFINN + Sentiment140 + NRC-Hash-Emo + SentiWordNet	0.58	0.15
LIWC + NRC Affect Intensity + SentiStrength + AFINN + Sentiment140 + NRC-Hash-Emo + SenticNet + SentiWordNet + Sentiment Emojis	0.59	0.15
LIWC + NRC Affect Intensity + SentiStrength + AFINN + Sentiment140 + NRC-Hash-Emo + SenticNet + SentiWordNet + Sentiment Emojis + 3≥gram≥1	0.68	0.13

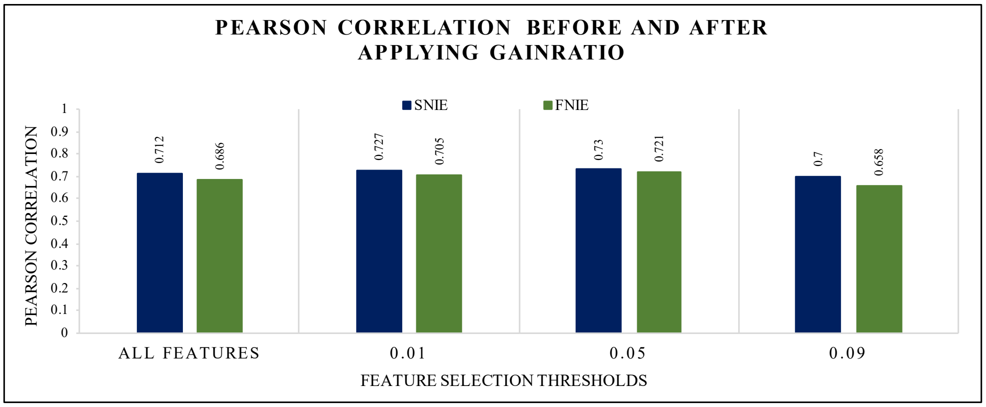


Figure 5.8: SNIE and FNIE Models accuracy before and after selecting the most predictive features using GainRatio.

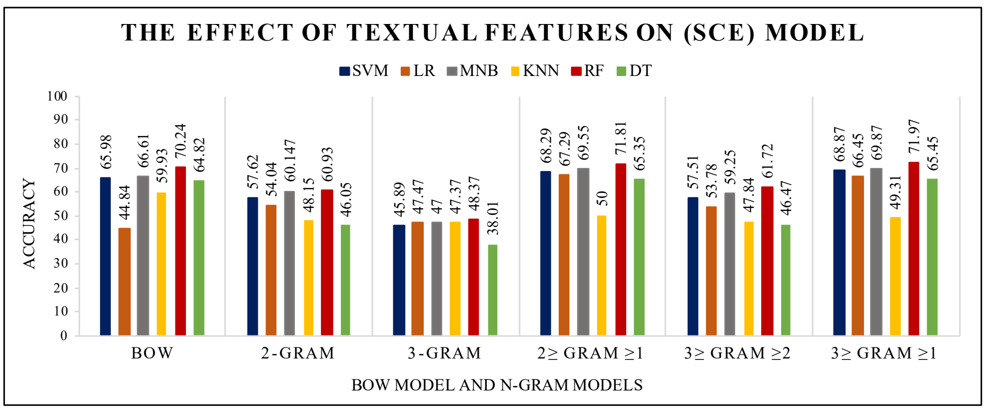


Figure 5.9: The effect of different textual features on the accuracy of the SCE model.

ually. Combining the 1-3gram model with the psychological features, including LIWC and CML lexicon, boosted the accuracy for most of the classifiers: SVM by 5.25%, MNB by 8.09%, LR by 3.16%, RF with3.52% and DT, 3.05 percentage points. Adding the sentiment and emotions-based lexicons, the frequency, and the sentiment of emoji to the previous features marginally increases the accuracy for MNB, LR and DT. MNB and LR achieved their best results by combining all the features, ending up with 72.34% and 69.50%, respectively. Experiment results showed that, in the case of using GainRatio with a 0.01 threshold, the accuracy was augmented for LR, K-NN and DT classifiers. At a 0.09 threshold value, the accuracy of MNB and SVM improved. As Table (5.8) shows, RF achieved the best result in evaluating social context (surrounding environment) when using the LIWC and LCM (DAVs, IAV, SV) psychological features in combination with textual features.

Table 5.7: Accuracy and F_{score} of the SCE model, comparing the use of different features.

	SVM		MNB		LR		K-NN		RF		DT	
Features	A	F	A	F	A	F	A	F	A	F	A	F
LIWC	64.72	0.63	62.61	0.62	64.61	0.64	62.88	0.60	70.50	0.70	60.04	0.59
LIWC + LCM (DAVs, IAV, SV)	64.61	0.63	62.46	0.61	64.77	0.64	63.61	0.61	71.45	0.71	60.41	0.60
LIWC + Emojis	65.08	0.64	62.61	0.61	64.77	0.64	62.88	0.60	71.81	0.71	60.19	0.60
Emotion Word Embeddings(EWE)	65.45	0.65	48.63	0.38	64.87	0.64	59.83	0.59	65.82	0.65	49.36	0.49
NRC Word-Emotion + NRC Hashtag Emotion	62.30	0.61	56.94	0.56	61.30	0.61	60.67	0.60	65.61	0.65	59.04	0.58
(MPQA, Bing Liu, NRC) Sentiment Lexicons + Sentiment Emojiss	57.30	0.54	52.36	0.52	56.46	0.55	57.67	0.57	62.14	0.61	62.09	0.62
NRC Word-Emotion + NRC Hashtag Emotion + (MPQA, Bing Liu, NRC) Sentiment Lexicons	64.40	0.63	58.88	0.58	63.14	0.62	58.25	0.57	70.66	0.70	61.98	0.61
LIWC + (MPQA, Bing Liu, NRC) Sentiment Lexicons + Sentiment Emojiss	65.98	0.65	61.88	0.60	65.14	0.64	62.93	0.60	71.81	0.71	61.30	0.61
LIWC + NRC Word-Emotion + NRC Hash Emotion	65.35	0.64	63.88	0.63	65.29	0.65	65.35	0.63	72.18	0.71	61.82	0.61
LIWC + NRC Word-Emotion + NRC Hash Emotion + (MPQA, Bing Liu, NRC) Sentiment Lexicons	65.56	0.65	63.82	0.62	64.93	0.64	64.61	0.62	71.97	0.71	60.83	0.60
LIWC + NRC Word-Emotion + NRC Hashtag Emotion + (MPQA, Bing Liu, NRC) Sentiment Lexicons + Emojis + Sentiment Emojiss	66.56	0.65	62.82	0.61	64.66	0.64	64.87	0.63	71.92	0.71	61.51	0.61
LIWC + 3≥gram≥1	70.76	0.70	71.92	0.71	68.19	0.67	59.83	0.57	74.65	0.74	65.72	0.65
LIWC + LCM (DAVs, IAV, SV) + 3≥gram≥1	70.60	0.69	71.97	0.71	68.45	0.68	59.72	0.57	75.70	0.75	64.87	0.64
LIWC + 3≥gram≥1 + NRC Word-Emotion + NRC Hashtag Emotion	70.66	0.70	72.02	0.71	69.13	0.68	59.41	0.56	74.55	0.74	63.82	0.63
LIWC + 3≥gram≥1 + NRC Word-Emotion + NRC Hashtag Emotion + (MPQA, Bing Liu, NRC) Sentiment Lexicons	71.03	0.70	71.50	0.70	68.29	0.67	59.51	0.56	74.76	0.74	63.88	0.63
LIWC + 3≥gram≥1 + NRC Word-Emotion + NRC Hashtag Emotion + (MPQA, Bing Liu, NRC) Sentiment Lexicons + Emojis + Sentiment Emojiss	70.87	0.70	71.60	0.70	69.45	0.69	59.51	0.56	73.86	0.73	65.03	0.65
LIWC + 3≥gram≥1 + NRC Word-Emotion + NRC Hashtag Emotion + (MPQA, Bing Liu, NRC) Sentiment Lexicons + Emojis + Sentiment Emojiss + POS	71.13	0.70	72.87	0.71	69.24	0.68	59.51	0.56	73.23	0.73	64.56	0.64
LIWC + LCM (DAVs, IAV, SV) + 3≥gram≥1 + NRC Word-Emotion + NRC Hashtag Emotion + Negation lexicon + (MPQA, Bing Liu, NRC) Sentiment Lexicons + Emojis + Sentiment Emojiss + POS + Emotion Word Embeddings(EWE)	70.87	0.70	72.34	0.72	69.50	0.69	60.98	0.58	68.76	0.68	64.03	0.64

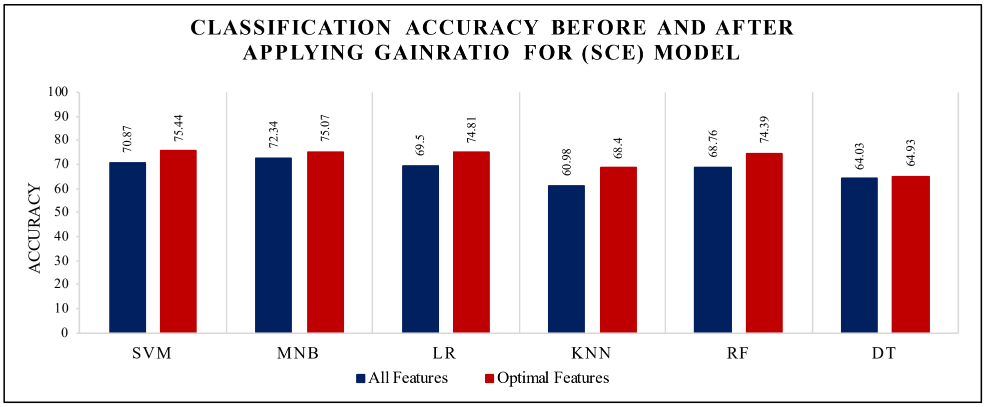


Figure 5.10: SCE Model accuracy before and after selecting the most predictive features using GainRatio.

Table 5.8: Accuracy, Recall (R), Precision (P) and F_{score} for the final NCR, NTI, NSM, SCE and LAI models.

Psychological need recognition models	Best classifier	Accuracy %	R	P	F
Need Content Recognition (NCR) Model	MNB	79.13	0.791	0.82	0.77
Need Type Identification (NTI) Model	SVM	81.97	0.81	0.82	0.817
Need Satisfaction level Measurement (NSM) Model	SVM	93.56	0.93	0.93	0.93
Social Context Evaluation (SCE) Model	RF	75.70	0.75	0.76	0.75
Life Aspect Identification (LAI) Model	LR	60.48	0.59	0.60	0.59

5.3.5 The Effectiveness of the Life Aspect Identification (LAI) Model

The experiment with textual features shows that the unigram model gives the best performance in identifying life aspect when compared to the bigram and trigram models, and also, with the combination of the models. This indicates that when identifying life aspect, it is not necessary to detect phrases and sequence of words, as in the previous need layers. Individual terms are more effective. Figure (5.11) provides a graphical comparison between classifiers using textual features. As Table (5.9) shows.Acceptable results were achieved for some classifiers using the LIWC lexicon, showing 51.69 % for SVM, LR with 51.65 %, and RF at 51.80%. Meager results are noted for MNB with 39.06%,K-NN at 36.97%, and DT coming in at 39.79%. Adding the eight life aspect lexicons improved the accuracy for all the classifiers. The experiments show that combining the unigram model with the LIWC lexi-

Table 5.9: Accuracy and F_{score} of the LAI model, comparing the use of different features.

	SVM		MNB		LR		K-NN		RF		DT	
Features	A	F	A	F	A	F	A	F	A	F	A	F
LIWC	51.69	0.48	39.06	0.33	51.63	0.49	36.97	0.35	51.80	0.48	39.79	0.39
LIWC + Life Aspect Lexicons	54.05	0.51	41.37	0.36	53.04	0.51	37.31	0.35	54.73	0.51	42.33	0.42
3≥gram≥1 + LIWC	54.73	0.54	55.97	0.54	56.82	0.56	42.16	0.39	54.17	0.50	48.13	0.47
3≥gram≥1 + Life Aspect Lexicons	55.07	0.54	57.72	0.56	54.67	0.53	45.26	0.42	55.46	0.53	46.22	0.45
3≥gram≥1 + LIWC + Life Aspect Lexicons	55.52	0.55	56.70	0.55	56.03	0.55	43.12	0.39	55.18	0.51	49.43	0.48

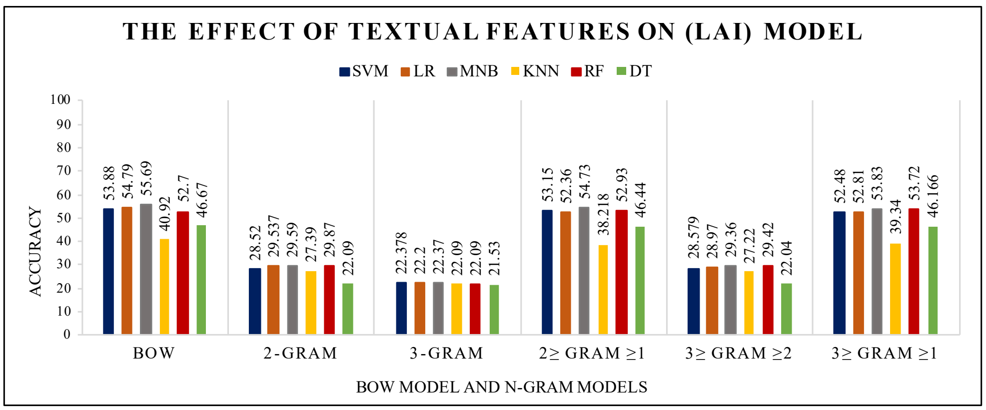


Figure 5.11: The effect of different textual features on the accuracy of the LAI model.

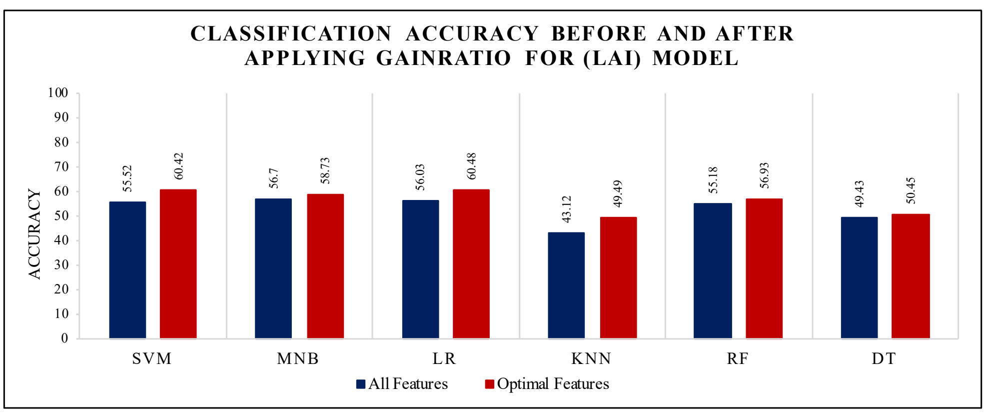


Figure 5.12: LAI model accuracy before and after selecting the most predictive features using GainRatio.

con optimized the accuracy for LR at 56.82%, while combining the unigram model with the eight life aspect lexicons provided the best accuracy rates for MNB with (57.72%), K-NN (45.26%) and RF (55.46%). For SVM and DT, combining all the features improved their accuracy to 55.52% and 49.43%. As Figure (5.12) shows, Eliminating the useless features as we measure a model's performance improved the accuracy rates for all the classifiers: SVM by 4.9%, MNB at 2.03%, LR by 4.25%, K-NN by 6.37%, RF by 1.75%, and DT by 1.02%. The best classifier in identifying the life aspect is LR with 60.48% accuracy as Table (5.8) illustrated.

Chapter 6

Case Studies: Recognizing Human Needs during Critical Events

The objective of this research is to take into consideration the basic and fundamental needs that are required for an individual to feel satisfied in order to promote well-being and prevent conflict and violence [18], [26]. The proposed psychosocial need recognition framework in Figure (6.1) could be used in a variety of applications.

For example, the identification of need types and assessment of satisfaction levels could be used in marketing and recommendation scenarios. A need-based recommender system could be developed using the psychosocial need recognition framework which would recommend products and services based on the detected individual need type. For instance, if the framework were to detect a dissatisfied competence need in an individual's life aspect, the need-based recommender system could recommend specific workshops, courses or any supportive service to satisfy the individual's competence need. Similarly, if a dissatisfied relatedness need was detected, the system might recommend movies, dating website or entertainment activities. Moreover, the framework could be used to measure an individual's daily psychological state of being in order to evaluate their overall life experience. Based on psychological need theories, many distinct psychological states and experiences such as psychological well-being, ill-being and high stress levels can be predicted, as illustrated in Figure (6.2). A considerable amount of experimental studies have proven that the satisfaction or unfulfillment of the three basic psychological needs can be significant indicators

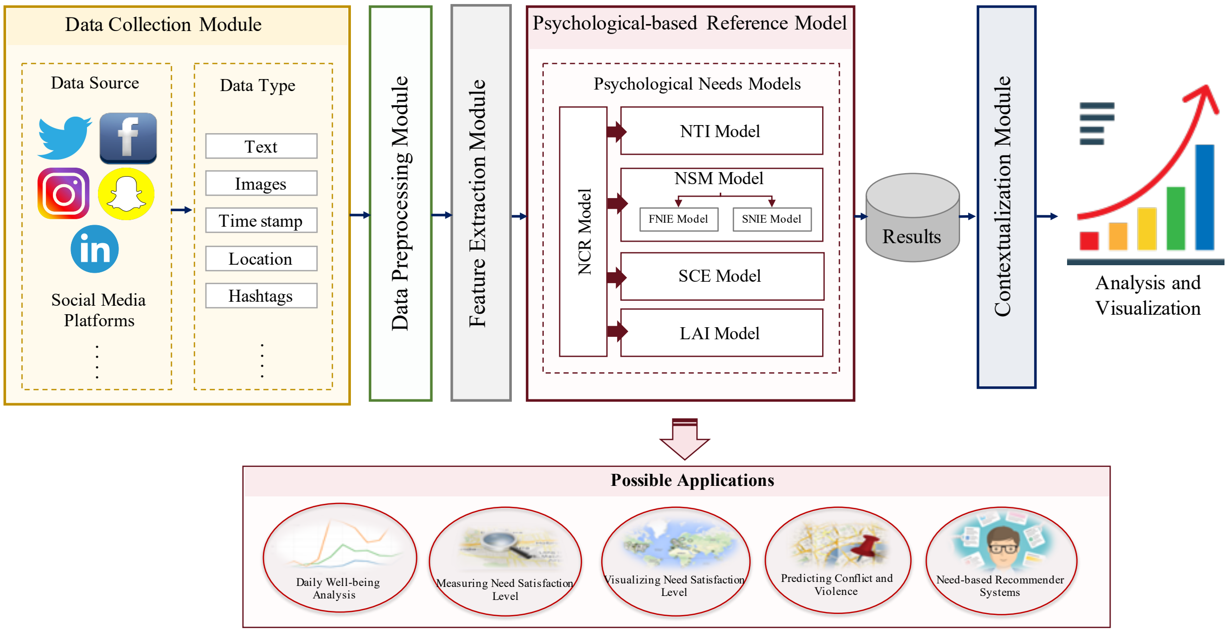


Figure 6.1: The psychological need recognition framework and its possible applications.

of an individual's quality of life [16]. Each one of these three needs can be utilized to determine and individual's state of being as they all have an independent and direct effect on an individual's emotional frame of mind in terms of personality traits and monetary experiences [87], [97]. Additionally, the framework can be useful in predicting high stress levels. The level of need satisfaction is associated with the way in which individuals deal with stressful situations. Individuals with a high level of need satisfaction are likely to feel less stressed, while those with low levels of need satisfaction are more likely to experience elevated stress levels.

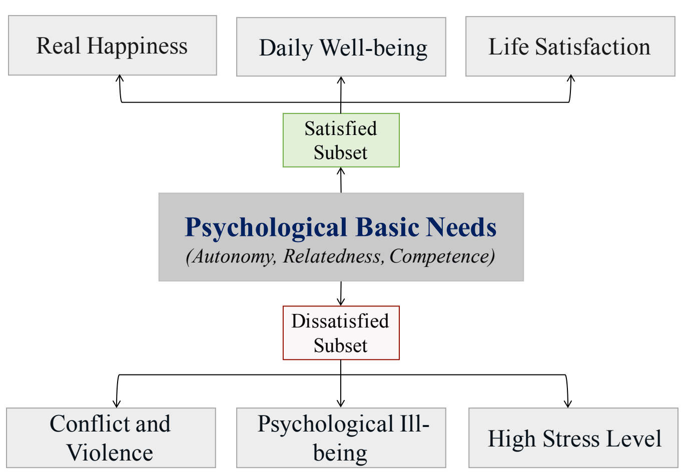


Figure 6.2: Psychological experiences associated with need satisfaction level.

Furthermore, human need theories provide valuable insight into the primary causes of conflict and the root of violence by claiming that unmet needs lead to unrest and contention. Since needs are innate, individuals and groups will do whatever they feel is necessary to satisfy their basic needs, even engaging in violence if they see no alternative. Rosenberg, in NVC, argued that violence is a tragic expression of unsatisfied needs. His model has since been used to solve conflict situations [8], [21] and [18]. Hence, the framework could be used by authorities to monitor citizen need satisfaction levels in order to improve situational awareness, and, in turn, take appropriate action in order to avoid conflict and violence. Moreover, the framework could be vital in evaluating the quality of life of individual citizens within a population by measuring their satisfaction levels regarding many life aspects, including education, work, health, and government. The resulting information could prove invaluable to city planners in modifying city services and plans while endeavoring to satisfy citizen needs. In this Chapter, we present two case study scenarios where we applied our proposed psychological need recognition framework to identify psychosocial need, measure satisfaction level and evaluate social context in response to critical and violent situations: Florida shooting event and New Zealand terrorist attacks.

6.1 Florida Shooting Event

We examine the public reaction to the recent shooting event which occurred in a school in Florida on Wednesday, February 14^{th}, 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 Data Preprocessing Module and Feature Extraction Module. Following these steps, the NCR 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 NTI model, the satisfaction level using NSM model, social context type using (SCE) model and life aspect using LAI model. Using the Contextualization Module, the results are analyzed 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 (6.1), and are sorted in descending order according to their frequency using Term Frequency (TF) score.
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 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 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 Figure (6.5) and Figure (6.6).

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 [5]. 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 [54]. In measuring an image's popularity, we consider the social attention factors of images that attract the audience. We calculate the social attention score (S_{attSco}) for each day of the event based on equation (6.1). Let i be the index for the T_{id} and assuming we have n T_{id}.

$$S_{attSco} = \sum_{i=1}^{n} (T_{rt} + T_f + T_r)_i \tag{6.1}$$

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 favourite, 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. Figure (6.7) shows the top four images ranked in descending order based on their (S_{attSco}) over the four days of Florida Shooting event and the March for Our Lives event.

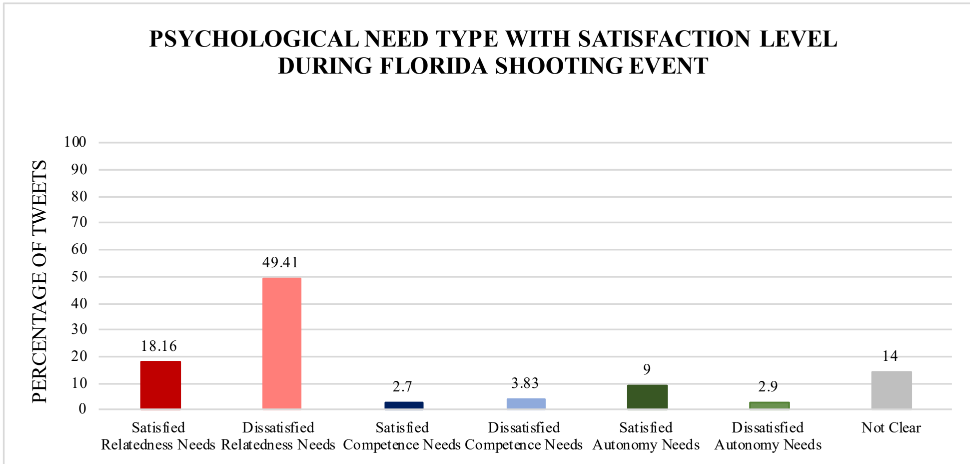


Figure 6.3: Using our framework to identify people's needs and measuring their satisfaction levels on the day of the Florida shooting and the subsequent three days.

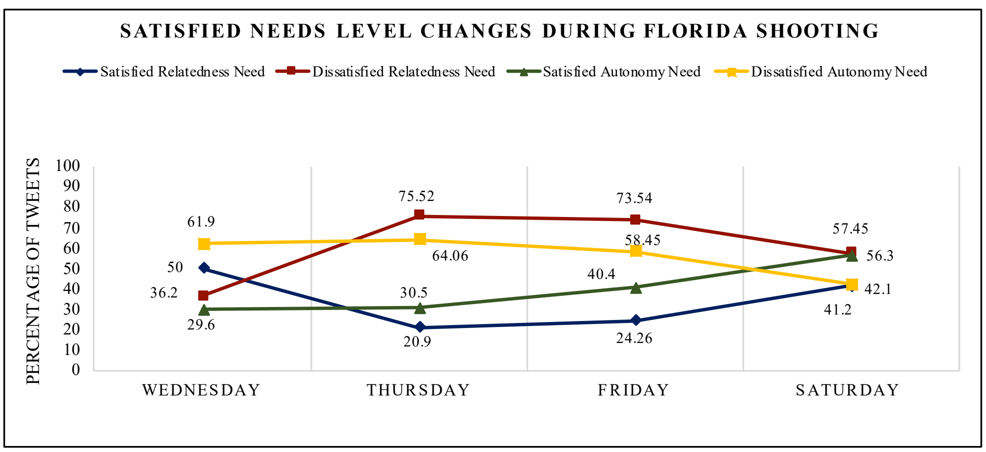
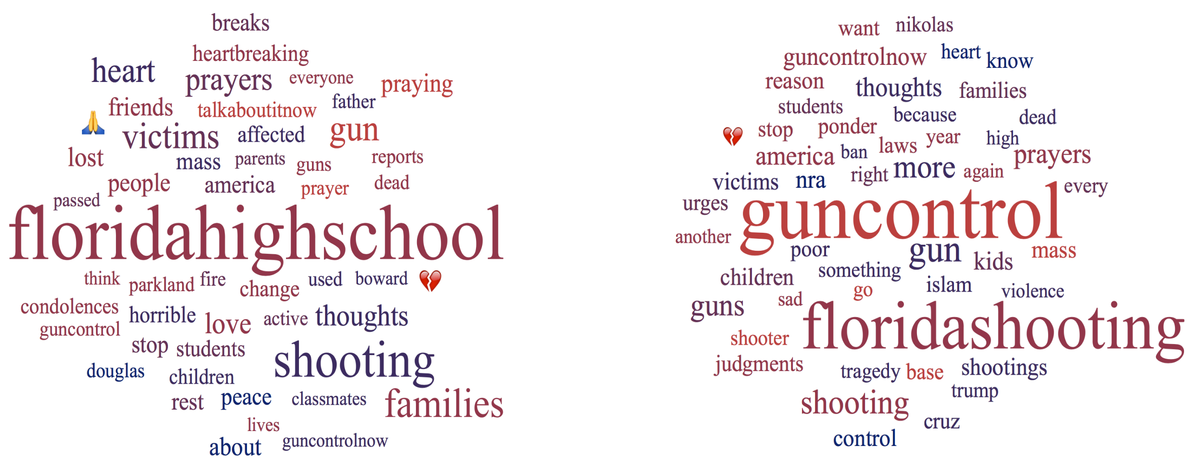


Figure 6.4: Measuring the changes in need satisfaction levels during the day of the shooting and the subsequent three days.

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%. Figure (6.3) shows 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.

Table 6.1: The top ten most frequently used hashtags during the Florida shooting event.

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



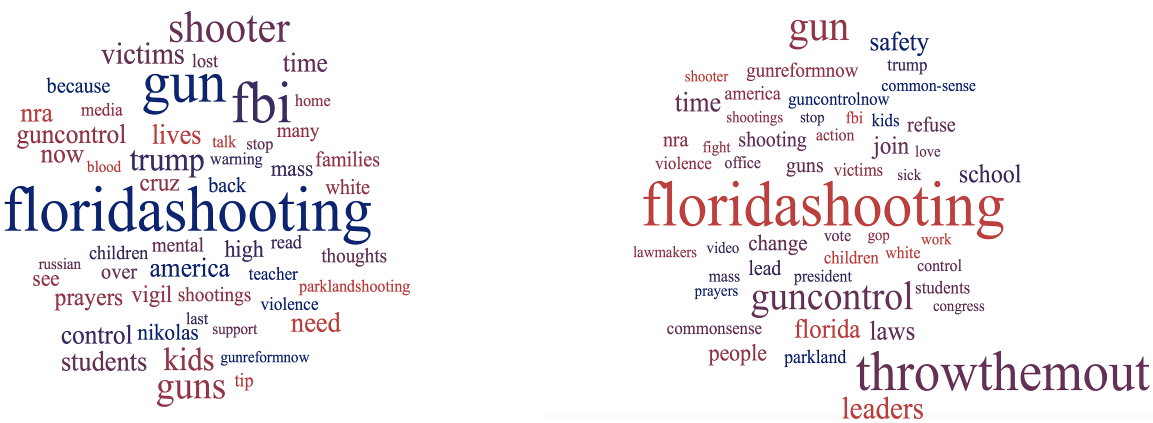
(a) (b)

Figure 6.5: Word cloud generated from tweets posted on Wednesday Feb, 14^{th} (a) and Thursday Feb, 15^{th} (b).

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. Figure (6.4) illustrates the changes of the relatedness 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 (6.1) shows, on Wednesday, the day of the shooting, people started talking



(c) (d)

Figure 6.6: Word cloud generated from tweets posted on Friday Feb,16th (c) and Saturday Feb,17th (d).

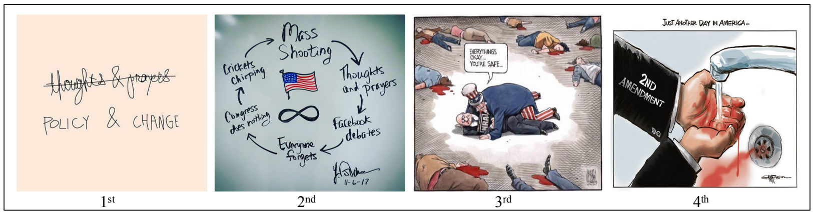
about the event using the #TalkaboutItNow and #Broward hashtags. Moreover, the sub-topics were centered around outpouring emotional hashtags such as #LoveisLouder, #Prayers, #RIP, #ThoughtsandPrayers and #Condolences, which illustrates the thematic focus of the tweets sent on the first day. As illustrated by the word cloud (a) in Figure (6.5), words such as "families", "prayers", "victims", "thoughts" and "hearts" were featured in a large number of tweets. As we can see in Figure (6.7) (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:

- *"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**

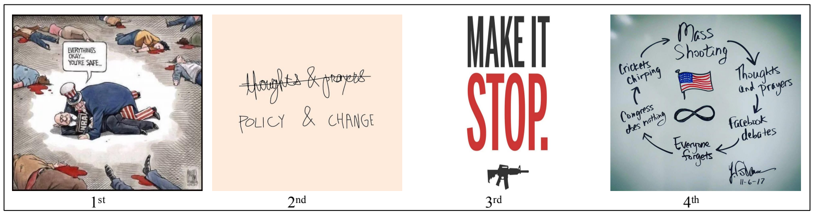
- *" These school shootings just make me more eager to become a teacher and do my part in never letting this happen again! #ParklandSchoolShooting #floridahighschool #standstrong"* - **Satisfied competence need**

- *"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**

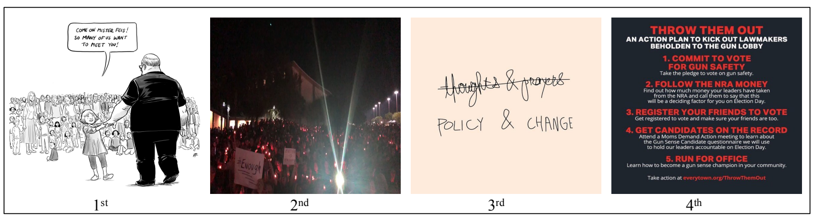
- *"when is enough going to be enough? how many innocent people - how many innocent*



(a) Top ranked images posted on Wednesday Feb, 14th



(b) Top ranked images posted on Thursday Feb, 15th



(c) Top ranked images posted on Friday Feb, 16th

(d) Top ranked images posted on Saturday Feb, 17th

(e) Top ranked images posted during March for our lives event

Figure 6.7: A chronological visual representation for the Florida shooting event and March for Our Lives event.

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 (6.1), 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 Figure (6.5). The visual representation in Figure (6.7) (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 (6.1) 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 Figure (6.6), 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 Figure (6.7) (c) shows, image depicting positive emotions towards a teacher who saved student lives achieved the most social attention. This is 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 Figure (6.7) (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. For example, the hashtags #ThrowThemOut, #StudentsDemandAction and #EndGunViolence were among the top 10 most used hashtags, as Table (6.1)

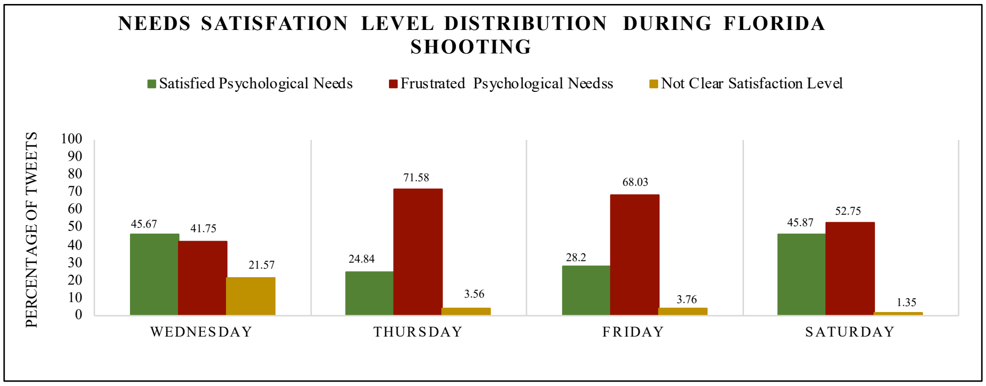


Figure 6.8: Identifying individuals' satisfied and frustrated needs during the Florida shooting using the NSM model.

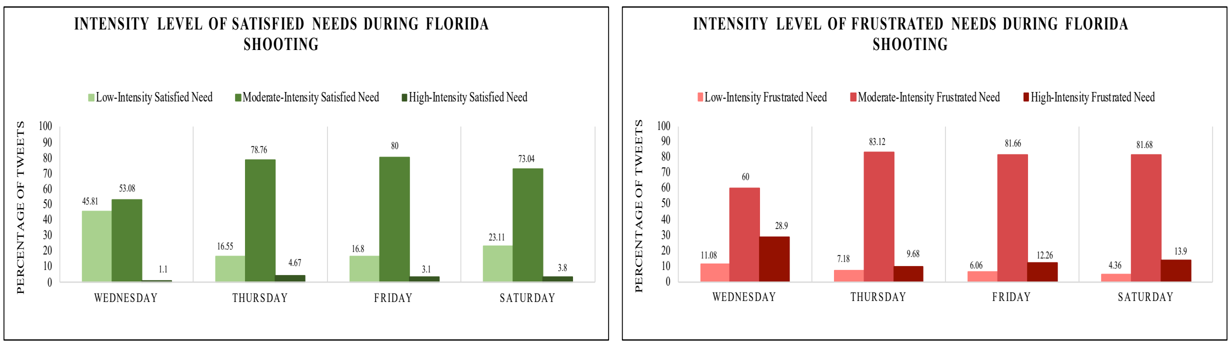


Figure 6.9: Intensity levels of satisfied and frustrated needs during the Florida shooting using the FNIE and SNIE models.

shows. The word cloud graph (d) in Figure (6.6) 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.

From the analysis we can see that the frustration levels experienced started at their lowest points in the first day, and increased through the following three days, as Figure (6.8) shows. Comparatively, satisfied needs, initiated at the highest level on the first day and fell over the following two days. Notably, as Figure (6.9) shows, high intensity frustration expressions appear more often than high intensity satisfied expressions, especially during the first day. In addition, low and moderate intensity emotional words are used more than high intensity words when describing satisfaction need levels, which clearly illustrates the level of happiness and satisfied in such event.

This 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 [8], 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 [33]. 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 Figure (6.4).

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 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**

Social context and surrounding environment affect a population's satisfaction levels. A supportive environment helps people to feel heard and safe, in turn, satisfying their needs. Non-supportive environments induce fear and unrest, resulting in high levels of frustration and directly affects need satisfaction in detrimental ways. As we can see from Figure (6.10), supportive social context was at its highest in the first day, as people supported each other while supporting the victims' families, and then decreased in the following days. Table (6.2) shows the most frequent sub-topics for the tweets classified as indicating a supportive environment, and non-supportive environment. For a closer look, the word cloud generated in Figure (6.11) shows the most frequent words exchanged during discussions on the first and last days.

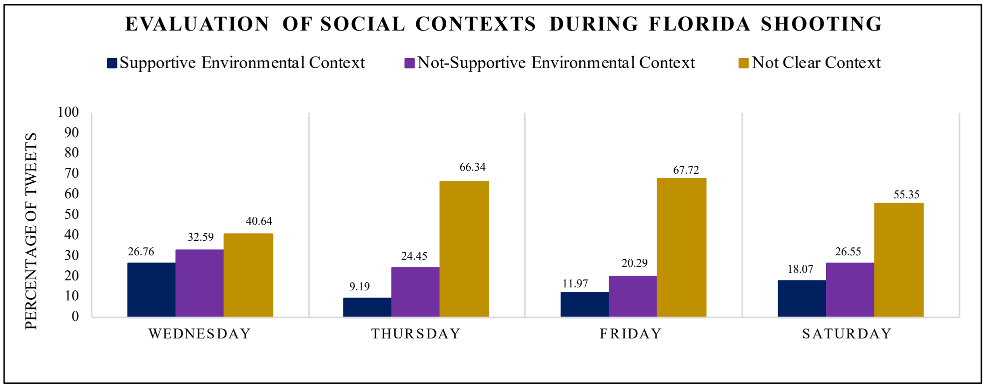


Figure 6.10: Identifying social context types using SCE model during Florida shooting event.

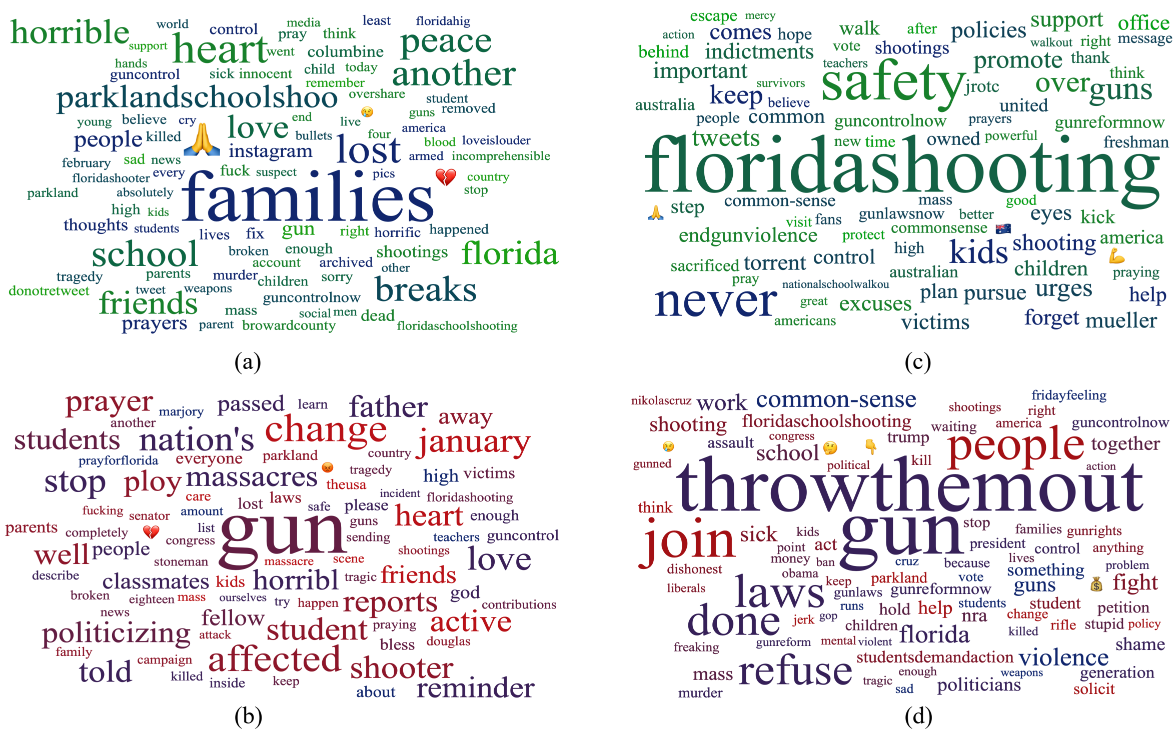


Figure 6.11: Word cloud generated from tweets which were posted on Wednesday (a),(b) and Saturday (c),(d) during the Florida shooting event, and were identified to have supportive social context (a),(c) and non-supportive social context (b),(d).

6.2 March For Our Lives Event

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

Table 6.2: The top ten most frequently used hashtags used in tweets classified to have satisfied and frustrated needs posted on Wednesday and Saturday.

Wednesday		Saturday	
Sub-topics for satisfied needs	Sub-topics for frustrated needs	Sub-topics for satisfied needs	Sub-topics for frustrated needs
1.#GunControl	1.#GunControl	1.#ThrowThemOut	1.#ThrowThemOut
2.#PrayForFlorida	2.#GunControlNow	2.#GunControl	2.#StudentsDemandAction
3.#GunControlNow	3.#DoNotRetweet	3.#ParklandStrong	3.#GunReformNow
4.#Prayers	4.#Instagram	4.#Endgunviolence	4.#GunControlNow
5.#Massacre	5.#LoveIsLouder	5.#2ndAmendment	5.#GunLaws
6.#MassShooting	6.#Incomprehensible	6.#NationalSchoolWalkOut	6.#GunRights
7.#PrayersAndLove	7.#StValentinesDayMassacre	7.#ColtonHaab	7.#2adefenders
8.#ThoughtsAndPrayers	8.#US	8.#Students	8.#NRA
9.#ValentinesDay	9.#AidanMinoff	9.#EmmaGonzalez	9.#NikolasCruz
10.#Victims	10.#CommonSenseGunLaws	10.#Pray	10.#GunViolence

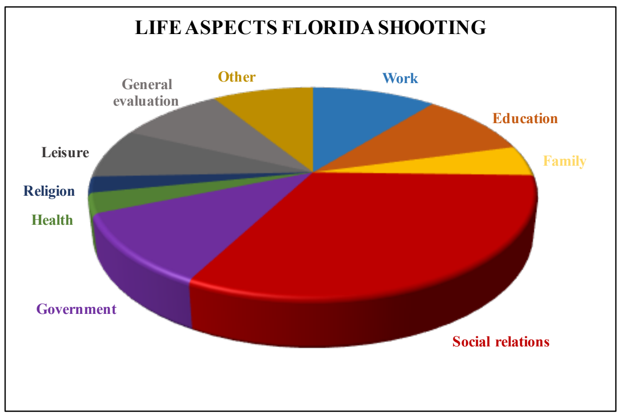


Figure 6.12: The identified life aspects extracted from tweets posted during the Florida shooting event.

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 NCR 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 NTI and NSM models. The analysis results aggregated based on the March for Our Lives event as overall.

The analysis in 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,

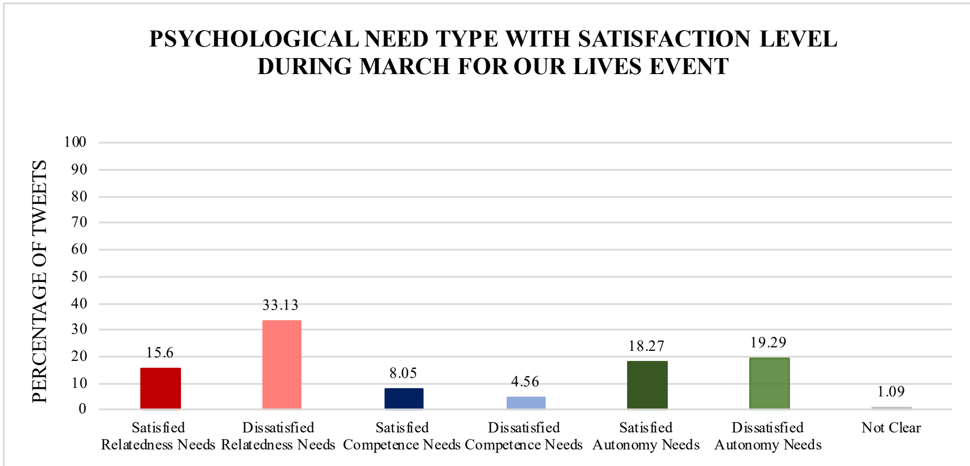


Figure 6.13: Identifying individuals' needs and measuring their satisfaction levels during the March For Our Lives event.

Figure 6.14: Word cloud generated from tweets posted during the March For Our Lives event.

as depicted in Figure (6.3). The demand for immediate action could contribute to this increase, where #NeverAgain is the most frequent hashtag used during this event, see Table (6.1). 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 Figure (6.13) shows, individuals ex-

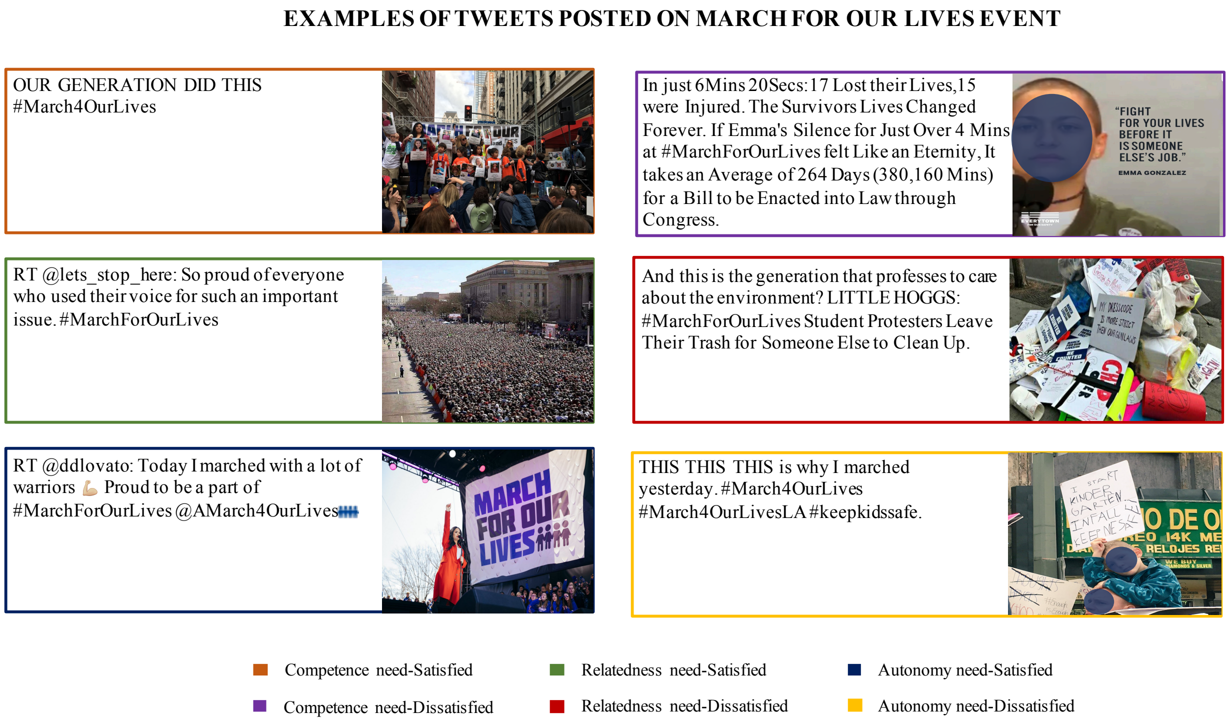


Figure 6.15: Random examples of tweets posted during the March For Our Lives event classified using our proposed framework.

press 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, 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 and any dynamic protest atmosphere were among the top ranked images over the duration of these events as shows in Figure (6.7) (e). As illustrated by the word cloud in Figure (6.14), 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. Figure (6.15) shows tweets combined with images posted during the March for Our Lives event classified using the proposed framework.

6.3 New Zealand Terrorist Attacks

In the second case study scenario, we analyze psychological needs for a similar event in order to compare public reactions based on event evolution and authorities' reactions. The Christchurch terrorist attack is a violent religion-based attack which occurred on March 15th, 2019. An Australian gunman orchestrated two consecutive mass shooting attacks on mosques during prayer in the city of Christchurch, New Zealand. 51 worshipers were killed and more than 40 injured. According to the news, the shooter published a racist manifesto detailing his motivations for the attacks on social media platforms. On Friday morning, he posted a tweet detailing his intentions to attack the two mosques saying: "I will carry out an attack against the invaders and will even livestream the attack via Facebook". Later in that day, he did, indeed, live-stream the first attack using Facebook's live service.

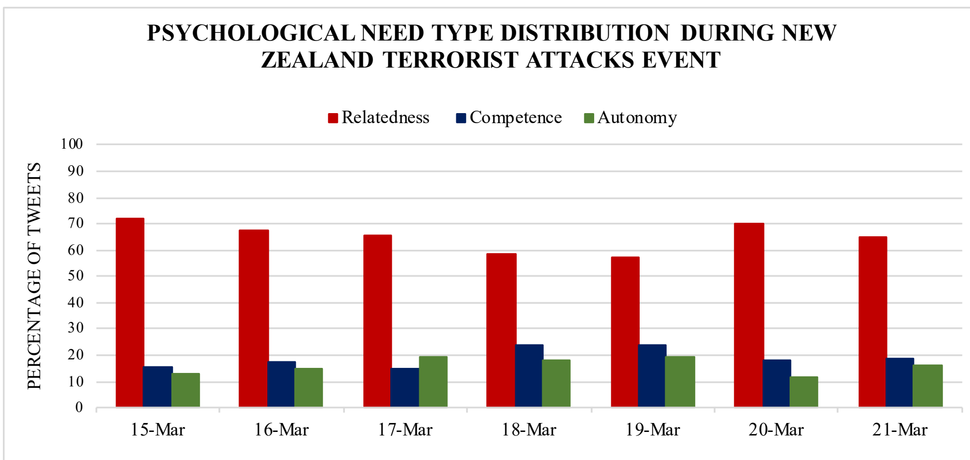


Figure 6.16: The need types identified during the New Zealand terrorist attacks using the NTI model.

We analyzed people's psychological needs during this event to illustrate how the dynamic evolution of the event (investigations, updates, authorities' responses and support) can affect and change a population's satisfaction levels. We collected tweets during the day of the event, as well as the following six days. We utilize all the possible event related hashtags such as #ChristchurchMosqueAttack, #NewZealandTerroristAttack and #NewZealand in order to retrieve tweets. This step allowed us to gather in the neighborhood of 85,000 tweets along with their attached images and meta data, including the post's geo-tagged location and time stamp. These tweets then went through the Data Preprocessing Module and Feature Extraction Module in each of the framework layers. The processed tweets were then fed to the NCR model to filter out useless tweets that did not

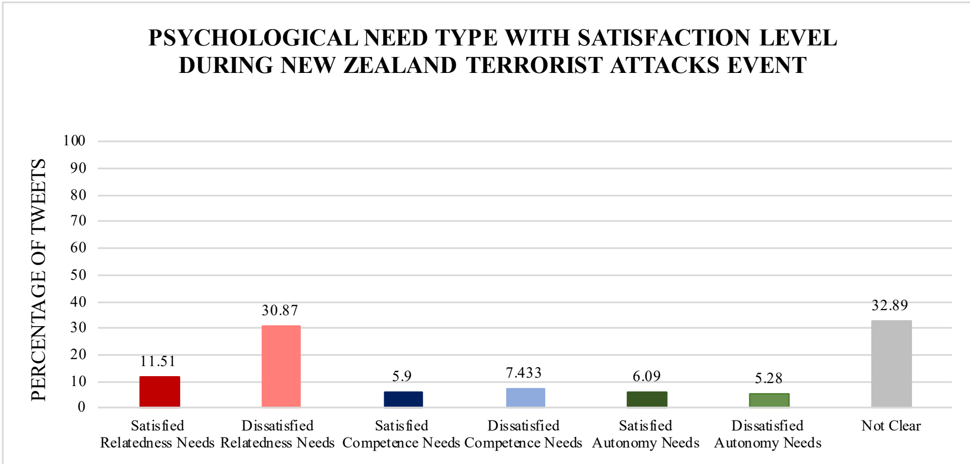


Figure 6.17: Identifying need types present during the New Zealand terrorist attacks using the NTI model, and measuring satisfaction levels using the NSM model.

express human needs. Around 13,675 tweets out of 85,000 were consequently ignored. The remaining 71,325 useful tweets which express people psychological needs were further analyzed to 1) identify need type using NTI model, 2) the satisfaction level using NSM model, 3) to evaluate the social context surrounding people using SCE model and 4) to identify life aspect of the expressed need using the LAI model. For a more in-depth analysis, we applied the SNIE and the FNIE Models in order to determine the intensity score of the satisfaction level.

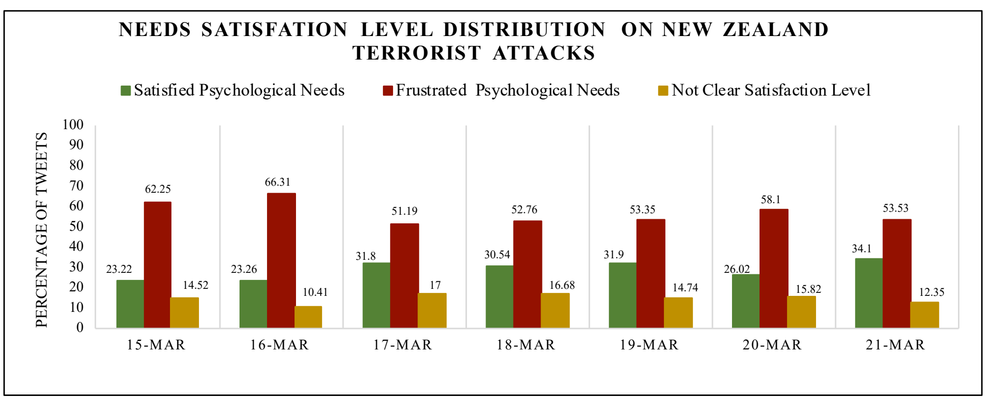


Figure 6.18: Measuring satisfaction levels using the NSM model during the days of the New Zealand terrorist attacks.

This analysis shows that, throughout this event, people expressed the relatedness need most, at (63.61%). The competence need followed at (19.57%), and autonomy need the least at (16.81%). As Figure (6.16) shows, among the seven days of the event, tweets representing relatedness need appeared more on March 15th, 16th and 20th. Competence

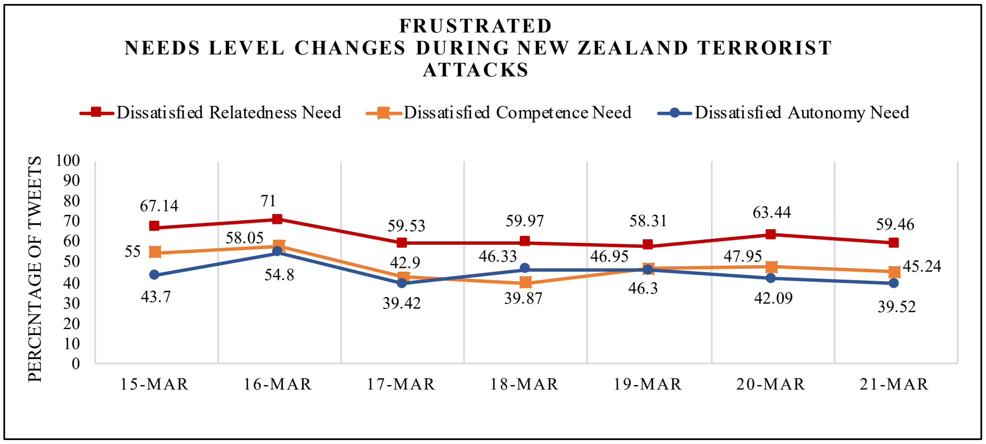


Figure 6.19: Measuring the changes in need frustration levels during the day of the New Zealand terrorist attacks and the subsequent six days.

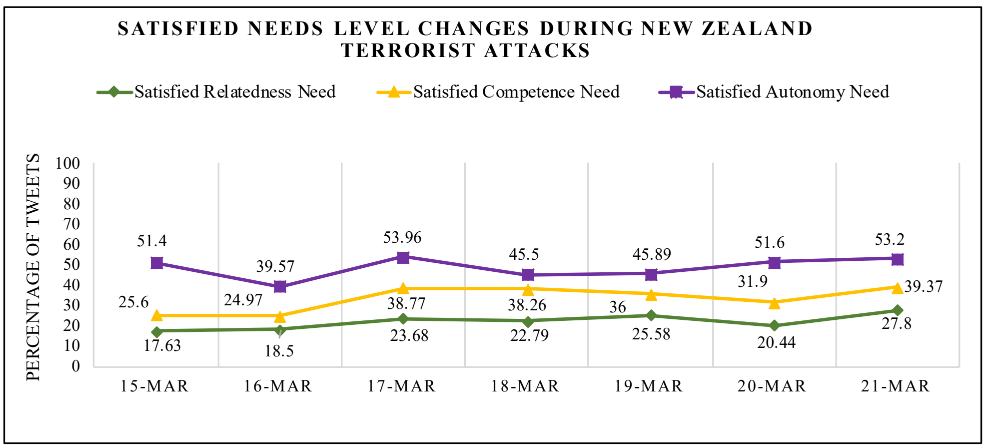


Figure 6.20: Measuring the changes in need satisfaction levels during the day of the Zealand terrorist attacks and the subsequent six days.

need related tweets appeared more on March 18th and 19th, where Autonomy need emerged more on March 17th. As Figure (6.18) shows, tweets posted during this event reveal that people feel frustrated (56.73%) of the time, where only (29.06%) of tweets expressed satisfied needs. The latter number rises on specific days as a reaction to certain happenings, which will be demonstrated in the details below. Roughly (32.89%) of tweets were classified to not have a clear satisfaction level and were, therefore, not considered in further analysis. Deeper analysis reflected a high frustration level of the relatedness need at (30.87%), among other need types such as competence need (7.43%) and autonomy need (5.28%), as shown in Figure (6.17).

Event progression, including police investigation updates, authorities' responses, and

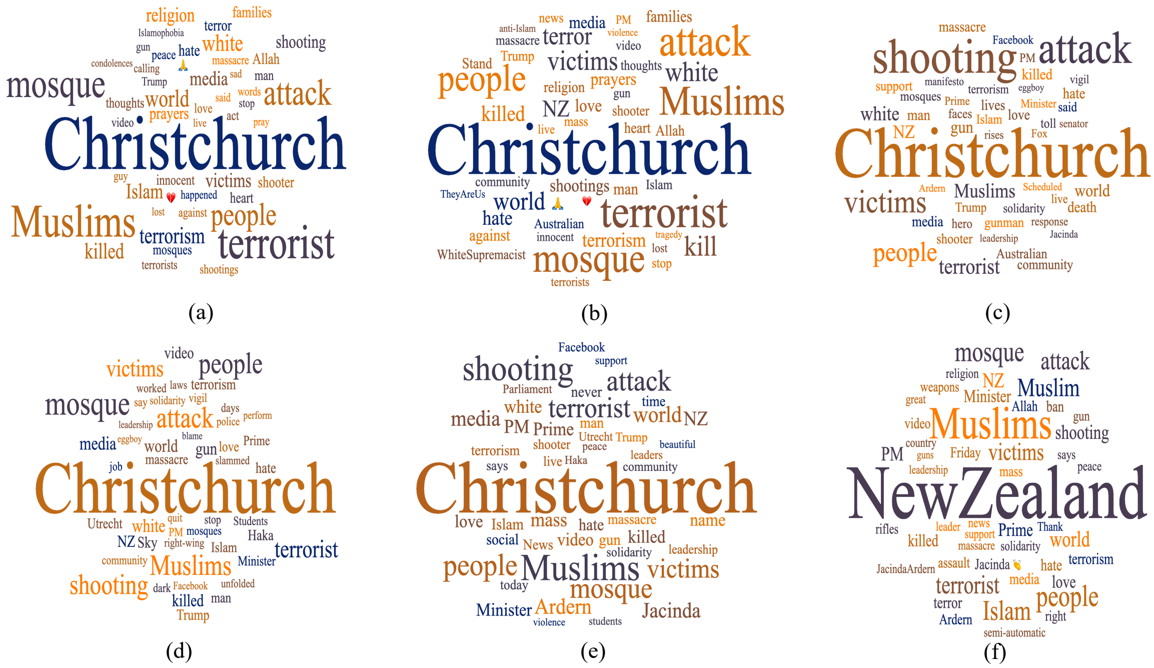


Figure 6.21: Word cloud generated from tweets posted on March, 15th(a), 16th (b), 17th(c), 18th (d), 19th (e) and March, 20th (f).

Figure 6.22: Word cloud generated from tweets posted on March, 21st.

surrounding support all affect human satisfaction levels; therefore, we used the same approach to create a timeline-based textual and visual representation to describe the event. We also relied on the news to understand the reasoning behind the use of some ambiguous hashtags and keywords which appeared frequently in the tweets. Figure (6.19) and Figure (6.20) illustrate the changes in need satisfaction levels for the identified need types of autonomy, relatedness and competence throughout the event.

Table 6.3: The top ten most frequently used hashtags during the New Zealand terrorist attacks event.

March 15^{th}	March 16^{th}	March 17^{th}	March 18^{th}	March 19^{th}	March 20^{th}	March 21^{st}
1.#Muslims	1.#Muslims	1.#Islamophobia	1.#Muslims	1.#Muslims	1.#Muslims	1.#Muslims
2.#Hellobrother	2.#Terrorist	2.#Muslims	2.#Islamophobia	2.#JacindaArdern	2.#JacindaArdern	2.#Islamophobia
3.#Terrorist	3.#WhiteSupremacist	3.#50lives	3.#EggBoy	3.#EggBoy	3.#Islamophobia	3.#Respect
4.#IslamoPhobia	4.#BrentonTarrant	4.#EggBoy	4.#Haka	4.#Islamophobia	4.#GunControl	4.#Peace
5.#BrentonTarrant	5.#WhitePrivilege	5.#TheyAreUs	5.#BrentonTarrant	5.#Terrorist	5.#NotEvenHisName	5.#GunControl
6.#PrayforNewzealand	6.#WhiteTerrorism	6.#JacindaArdern	6.#FarRight	6.#Solidarity	6.#Terrorist	6.#HeadScarfForHarmony
7.#Rip	7.#HelloBrother	7.#WhiteSupremacy	7.#Terrorist	7.#Haka	7.#Utrecht	7.#JacindaArdern
8.#BreakingNews	8.#Islamophobia	8.#Terrorist	8.#Trump	8.#Facebook	8.#Guns	8.#NotEevenHisName
9.#Facebook	9.#WhiteSupremacy	9.#PrayForNewzealand	9.#JacindaArdern	9.#NotEvenHisName	9.#Hijab	9.#BanAssaultWeapons
10.#MuslimsareNotTerrorist	10.#49lives	10.#FraserAnning	10.#TheyAreUs	10.#Trump	10.#Haka	10.#LeadreShip

On March 15^{th}, the day of the attacks, most tweets posted expressed a high frustration level for all the three needs: relatedness (67.14%) Autonomy (43.7%) and Competence (55%). Less than half of the tweets expressed satisfied needs. On this day, people immediately started categorizing the event as a religious/racist related attack, as reflected in the word cloud (a) in Figure (6.21). They used hashtags such as #muslims, #terrorist, #islamophobia, #breakingnews, #muslimsarenotterrorist and #brentonTarrant (shooter's name), as can be seen in Table (6.3). They expressed their prayers and condolences to the victims and their families using #pray for New Zealand and #rip hashtags. Also, people used #Facebook to talk about the shared livestreamed video for the two attacks. Through the news, we came to understand the usage of #hellobrother, which was among the top ten hashtags. *"Hello Brother"* were the last words of the first victim of the shooter before he was shot and killed. An image with the *"Hello Brother"* title was the most shared image on that day.

Frustration levels for all the three needs escalated to their highest on the second day, March 16^{th}, where relatedness needs reached (71%), competence (58.05%) and autonomy (54.8%). The satisfaction level deteriorated on this day, especially for Autonomy need (40.18% to 39.57%). Hashtags such as #whitesupremacist,#whiteprivilege, #whiteterrorism and #whitesupremacy were among the most frequent hashtags describing the shooter's motivation behind the attack. Moreover, #49lives emerged that day to count and update the loss of lives. As Figure (6.25) shows, the shooter's image was prominent in the image collections on the second day, as well as another magazine picture depicting similar attack events in different ways.

On March 17^{th}, there was a noticeable change in the need satisfaction levels. Tweets

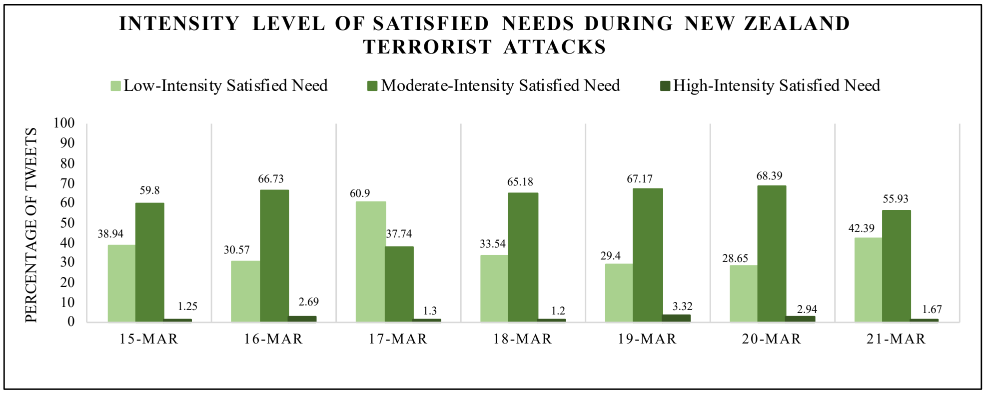


Figure 6.23: Intensity levels of satisfied needs measured during the New Zealand terrorist attacks using the SNIE model.

expressing dissatisfied needs dropped significantly for all the three needs: (11.47%) in relatedness needs, (15.38%) in autonomy and (15.15%) in competence needs, as figure (5) shows. Moreover, in Figure (6.24), we can see that the usage of dissatisfaction expressions with high and moderate intensity level in tweets presented less than the previous days. There was also an increase in the number of tweets expressing satisfied needs for all the three need categories, reflecting less intense emotional expressions, as Figure (6.23) shows. Satisfied relatedness needs increased by (5.18%) competence need increased by (13.8%) and autonomy need increased by (14.39%). As Table (6.3), word cloud (c) in Figure (6.21) shows, new topics of conversation arose centering around the prime minster's responses during her statement using #jacinda ardern, #theyareus and #50lives. Moreover, #eggboy and #fraseranning trending on Twitter on that day garnered worldwide attention. People shared their feelings and opinions about the actions the youth took in response to an Australian politician's comment regarding the New Zealand attack during a live interview on March 16$^{\text{th}}$, where the Australian Senator blamed the New Zealand shooting on immigration. Images illustrating support, solidarity and emotional reactions were among the most frequent images shared on that day, even more so than the first and second day.

On March 18$^{\text{th}}$ and 19$^{\text{th}}$, there was no significant change except a drop in satisfied autonomy need, from (53.96%) to (45.89%), and an increase in their frustration autonomy needs by (7.53%) percentage points. New hashtags in the tweet collection gathered on March 18$^{\text{th}}$ and 19$^{\text{th}}$ include #haka, #trump, #far-right, #solidarity, #facebook and #notevenhisname lead the public conversation and discussion. We scrutinized the news and the complete tweet textual messages to decode the appearance of some ambiguous or unclear hashtags among the most frequent hashtags. For example, #haka, references a ceremonial dance, in which people perform to honor the victims as a mark of sympathy

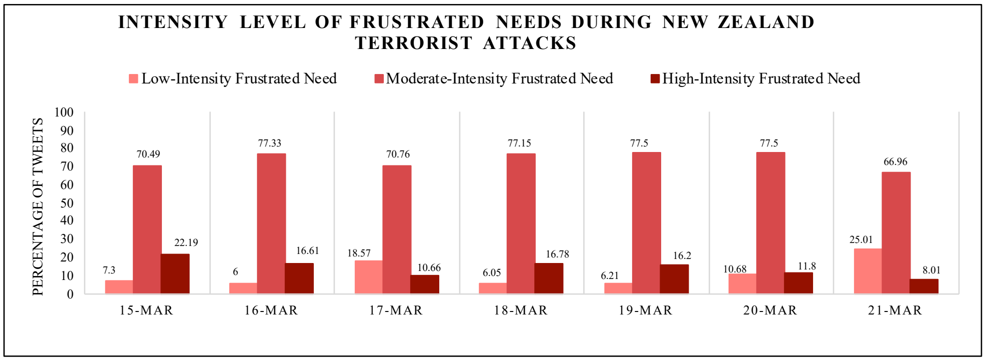


Figure 6.24: Intensity levels of frustrated needs measured during the New Zealand terrorist attacks using the FNIE model.

and solidarity. The #notevenhisname is a phrase that the New Zealand prime minster used in her statement on March 17^{th}, where she refused to mention the shooter's name. In addition, People used #Trump most frequently to report their opinion concerning his responses/tweets regarding the attacks. In regard to the hashtag #facebook, Facebook released a statement explaining their actions towards the shared video and how they planned to set some rules to reduce online hate and violence content in future. This coming in the aftermath where Facebook faced global reaction in response to their failure to prevent the attack being livestreamed. Many big name companies stopped advertising on social media platforms, including Twitter and Facebook, due to the failure to identify and detect hate content. This mainly supports our hypothesis on how analysing social media content could help prevent the facilitation of violent behaviour leading to tragic events. The word cloud (c) presented in Figure (6.21) shows the most frequently used words and phrases on these days. Images showing support and solidarity still prevail in the image collection as Figure (6.25) shows. The following tweets were posted on March 18^{th} and March 19^{th}.

On March 20^{th}, the autonomy needs changed noticeably and in opposition to other needs. The satisfied autonomy need heightened by (5.71%), and the dissatisfied autonomy need dropped from (46.3%) to (42.09%). In contrast, satisfied relatedness need depreciated slightly by (5.14) points, and competence needs fell by (4.1), while the dissatisfaction increased, especially for relatedness needs, by (5.13%). On that day, as can be seen from Table (6.3), #guns,#hijab, #Utrecht and #guncontrol are new hashtags, leading the subtopic of discussion. On the fifth day after the shooting, New Zealand Prime Minister, Jacinda Ardern, announced a plan to reform gun law, banning all military-style semiautomatic weapons. This may explain the higher expressions of satisfied autonomy needs and the lower expression of dissatisfied autonomy needs tweets posted on this day. Moreover, #hijab was used more frequently, where non-Muslim women showing their caring and

(a) Top ranked images posted on March, 15th.

(b) Top ranked images posted on March, 16th.

(c) Top ranked images posted on March, 17th.

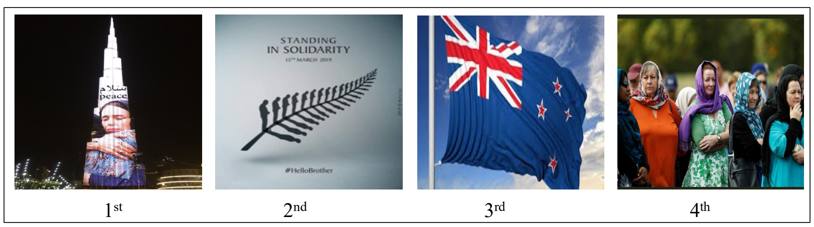
(d) Top ranked images posted on March, 16th.

Figure 6.25: A chronological visual representation for the New Zealand terrorist attacks.

support. #Utrecht was used frequently on March 19th; furthermore, it climbed to be one of the ten most frequently used hashtags on this day. People used #Utrecht in reference to another shooting attack in Utrecht, Netherlands, which occurred on March 18th, 2019, where a man opened fire on a tram killing three people and injuring seven. Tweets posted on this day mentioned the two attacks, comparing how the news and media reported them differently based on the religion and nationality of the attackers. The visual representation in Figure (6.25) shows how images reflecting support and solidarity continue to lead the visual collection/representation.

(a) Top ranked images posted on March, 19$^{\text{th}}$.

(b) Top ranked images posted on March, 20$^{\text{th}}$.



(c) Top ranked images posted on March, 21$^{\text{st}}$.

Figure 6.26: A chronological visual representation for New Zealand terrorist attacks.

On Thursday, March 21$^{\text{st}}$, within all three need categories, people satisfaction levels increased, and their frustration levels decreased. They also expressed less moderate and high intensity frustration words and more low intensive language compared to the beginning of the event, as Figure (6.24) shows. New sub-topics mentioned that day were: #respect, #peace, #headscarfforharmony, #leadership and #banassaultweapons. On this day, women announced a "scarves in solidarity" event to be hold on Friday using the hashtags #headscarfforharmony, #respect, #peace and #leadership hashtags were mentioned frequently in tweets talking about the NZ prime minster's speech and how people in new Zealand supported and dealt with that tragic event.

Gauging the intensity of the language used in posts to express satisfaction and frustration needs gave us a deeper understanding of the population's feelings and reactions in regards to their levels of satisfaction versus frustration. As we can see from Figure (6.24), people used high and moderate emotional expressions to convey their frustration level, which revealed how angry they were throughout the event. On the other hand, they used

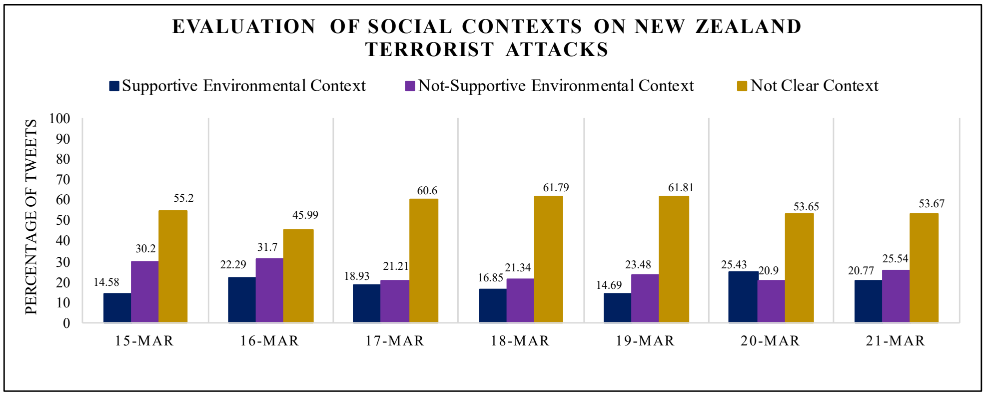


Figure 6.27: Using the SCE model to identify social context types during the New Zealand terrorist attacks.

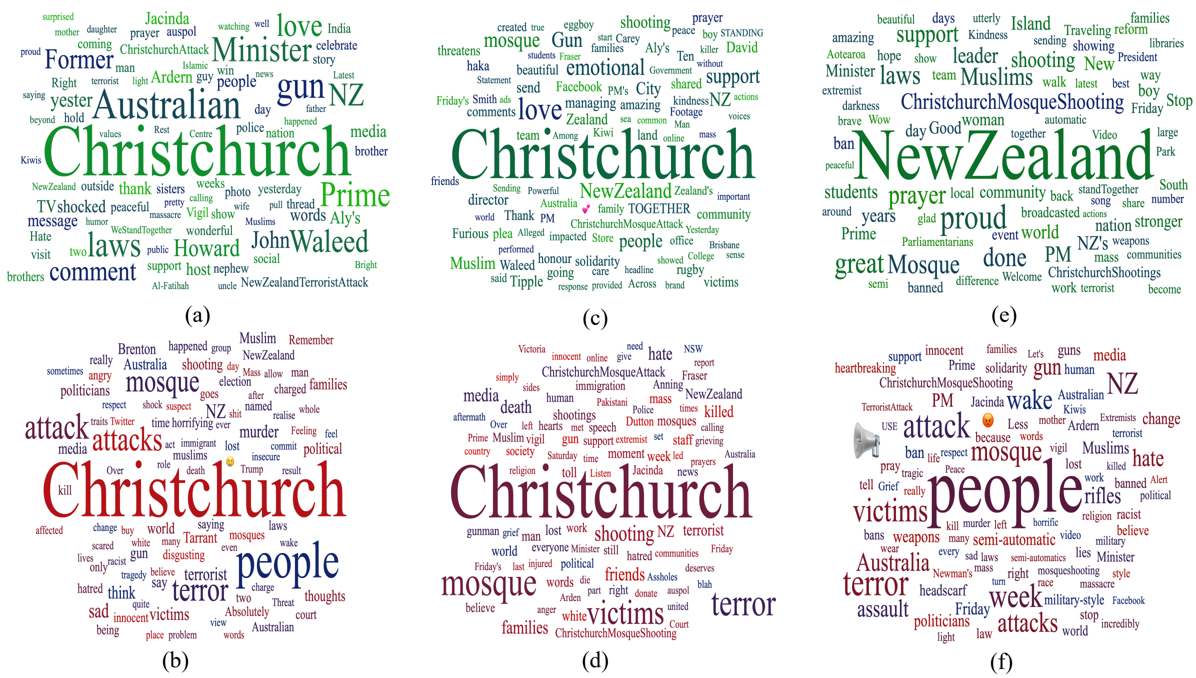


Figure 6.28: Word cloud generated from tweets which were posted on March15th (a), (b), March17th (c), (d) and March 21st (e), (f), during the New Zealand terrorist attack, and were identified to have supportive social context (a), (c), (e) and non-supportive social context (b), (d), (f).

expressions between low and moderate intensity levels to communicate their satisfaction level. Very few high intensity satisfaction expressions were reflected during this event, as Figure (6.23) shows.

For social context analysis, Figure (6.27) shows how people in New Zealand observe

Table 6.4: The top ten most frequently used hashtags classified under supportive social context and non-supportive social context posted on March 15th, March 17th and March 21st during the New Zealand terrorist attacks event.

March, 15th		March, 17th		March, 21st	
Supportive Social Context	Non-Supportive Social Context	Supportive Social Context	Non-Supportive Social Context	Supportive Social Context	Non-Supportive Social Context
#Auspol	#Immigrant	#EggBoy	#Auspol	#Gun	#BackStronger
#ABC	#Muslims	#Muslims	#50lives	#JacindaArdern	#Boycott
#Kiwis	#Australian	#EggBoyForPM	#FarRightExtremism	#KiaKaha	#FraserAnning
#NewZealand	#MosqueMassacre	#JacindaArdern	#IslamoPhobia	#NZFirst	#Hate
#PennyWong	#PeacefulMosques	#NaeemRashid	#Muslims	#StoptheRacism	#HeartBreaking
#WeLoveOurPeople	#Terrorism	#TheyAreUs	#NZMosqueShooting	#TheyAreUs	#Politics
#WeStandTogether	#Auspol	#Kindness	#Funerals	#StandTogethe	#Terrorist
#Respect	#Chchshooting	#Love	#Trump	#FightHateWithLove	#TheyAreUs
#TheMuslimPhotographer	#Respect	#Solidarity	#NZpol	#2MinutesSilence	#NZGovernment
#WeAreYou	#TheyAreUs	#StandTogether	#White	#Auckland	#Banned

their surroundings and evaluate their social context. We notice that the day of the event and the next day, people reported that they did not perceive a supportive environment, at percentages of (30.2%) on March 15th, and 31.7 on March 16th, which are the highest when compared to the other days. This confirms that their frustration was at its highest level in the first two days, as shown in Figure (6.18). Tweets reflecting that people identify their environment as non supportive appeared less often by March 17th and March 20th. The highest volume of tweets expressing supportive social context came on March 20th. On that day, and for the first time, people posted tweets indicating that they felt they had a supportive environment more than non-supportive environment. This affirms our statement that certain sub-events during these days, such as the prime minster's official speech on March 17th, and the announcement of a plan for gun law reform on March 20th, could be the reasons for the elevation in tweets indicating supportive social context. Table (6.4) shows the most frequent sub-topics (hashtags) posted on March 15th, 17th and 20th. The word cloud in Figure (6.28) includes the most frequent words used on these days (a) and (b) for March 15th, (c) and (d) for March 17th and (e) and (f) for March 21st.

As a situation unfolds, people analyze event details based on their points of view, which are influenced by different factors such as: age, gender, race, culture, religion, interests and many others. These factors have a significant impact on the way people perceive

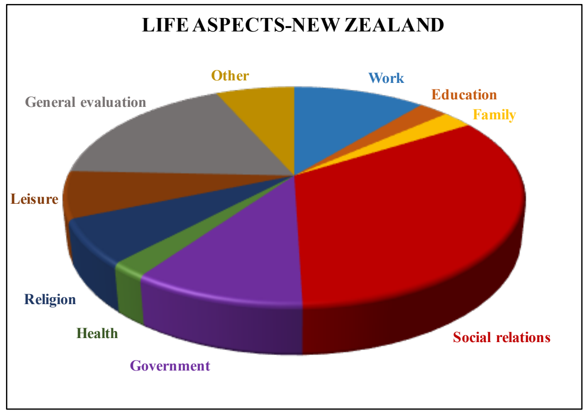
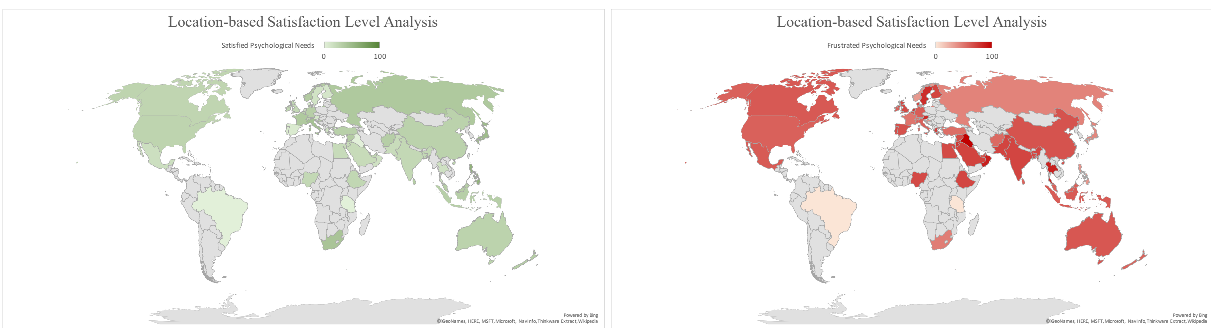


Figure 6.29: Identified life aspects extracted from tweets posted during New Zealand terrorist attacks event.



(a) (b)

Figure 6.30: Measuring individuals' satisfaction levels using tweets generated from within Canada, United States and Middle East during the New Zealand terrorist attacks.

any particular situation and how it affects them. Accordingly, the posts gathered during the New Zealand incident bring to light the diverse angles from which each individual's perception is generated. This diversity is illustrated through the tweet categorization in Figure (6.29) .

An individual's geographical location and cultural observations may have an impact on needs. Therefore, we analyze need satisfaction level based on location (where they were when they posted the tweets sharing their feelings and needs). Figure (6.30) (a) and (b) show location-based analysis for need satisfaction levels. We selected Canada and the United States (combined) and Middle East countries. In Canada and the United States, (32.39%) of tweets reveal that people were satisfied; whereas, (52.23%) of tweets express frustrated needs. In Middle East countries, (28.01%) of the posted content indicates that people felt satisfied, where (55.95%) shows frustrated needs. Table (6.5) shows the most frequent sub-topics discussed when population needs were satisfied vs frustrated in the two

Table 6.5: The top ten most frequently used hashtags identified as reflecting satisfied needs or dissatisfied needs posted within Canada, United States and Middle East.

Middle East		Canada and United states	
Sub-topics for satisfied needs	Sub-topics for frustrated needs	Sub-topics for satisfied needs	Sub-topics for frustrated needs
#HelloBrother	#HelloBrother	#Muslims	#WhiteSupremacist
#Muslims	#Terrorist	#EggBoy	#WhitePrivilege
#PrayforChristchurch	#Muslims	#WhiteSupremacist	#Islamophobia
#هجوم_نيوزلندا_الإرهابي	#Islamophobia	#prayforchristchurch	#WhiteSupremacy
#Islamophobia	#Media	#Islamophobia	#BreakingNewsNow
#Istanbul	#WhiteSupremacist	#AllahuAkbar	#WhiteTerrorism
#JacindaArdern	#حادث_نيوزلندا_الإرهابي	#CAIR	#Muslim
#Jesus	#Australia	#PrayForChristchurch	#Terrorist
#Kuwait	#BrentonTarrant	#OneTeamOneFight	#FacebookMassacre
#Quran	#Islam	#JacindaArdern	#WhiteNationalist

locations during the first three days of the event.

6.4 Discussion

The results achieved using our human need recognition framework in comparing the two case studies show that human reaction differs in direct correlation with each individual event's evolution and authorities' immediate responses to their needs. The frustration level in the first case study: Florida shooting in Figure (6.8) is higher than the second case New Zealand in Figure (6.18). During the Florida shooting, people demanded action from authorities in regards to gun control laws right from the day of the shooting, with discontent and anger continuing to rise through to the fourth day. During times such as these, people are afraid, which leads to frustration and dissatisfaction, which, in turn, leads them to take action (come together and protest in order to raise their voices). Their expression on social media platforms is their way to shed light on and satisfy their needs in a safe way; whereas, some people may choose violence if there is no alternative way to meet their needs, as the psychological research addresses [33]. In contrast, in the second case, from the first day, the prime minster, on March15$^{\text{th}}$, committed to take action in changing gun control laws to ensure the safety of the citizens of New Zealand. On March17$^{\text{th}}$, she said: "There Will Be Changes to Gun Laws", which may explain the noticeable changes in people satisfaction levels on that day. On March 20$^{\text{th}}$, the news reported that the gun law was changed, and all military-style semi-automatic weapons are now banned. As can be seen from the second case, the authorities' immediate responses and actions positively affect satisfaction levels. Figure (6.4), we see that the frustration level during the Florida shooting started at its lowest, and increases through the following three days. In contrast, frustration levels in New Zealand start at its highest level in the first two days and decreases over the following days, as Figure (6.19) shows. In both the Florida shooting and the New Zealand attack, during the first day, the highest intensity dissatisfaction expressions dominated posts, as Figure (6.9) and Figure (6.24) illustrates. In the subsequent days, most of the expressions of frustration were recognized to be at moderate intensity levels. During the New Zealand attack, with time, people used less high intense and more of the lower intense dissatisfaction vocabulary as can be seen from Figure (6.24). On the contrary, during the Florida shooting, over time, people used higher intense and less low intense emotional words to express their feelings. Therefore, our proposed human needs recognition framework can help authorities to monitor and analyze a population's needs at any time, any event and any location in the hopes of preventing conflict and violence; and also, to assure quality of life. In addition, they could interpret how people perceive their surrounding environment in order to recognize and understand the grounds of a population's discontent and determine the appropriate actions.

Chapter 7

Conclusion and Future Work

7.1 Conclusion

The interpretation of data garnered through the proposed psychological needs recognition and analysis can assist authorities; providing a heightened situational awareness and improving management of pre and post-event conflict and social reactions. These methods could prove especially effective in smart city research and development. In this thesis, we design, implement, and evaluate a theoretical-based multi-layered reference model, which is capable of identifying human psychological needs, and ascertaining their satisfaction level, evaluating people surrounding environment with regard to various life aspects. The design and the development of the reference model layers is influenced by motivational psychology research. We have introduced a basic psychological needs corpus consisting of 18,847 tweets, 34% of which (around 6334 tweets) capture explicit and implicit human needs expressions and convey psychological basic needs. The corpus was annotated, identifying psychological needs, levels of satisfaction of the needs, types of social contexts and life domains. These annotations were performed manually by psychologists. Several techniques were utilized to encourage high-quality annotations, including the design of an annotation guideline based on several validated psychometric surveys and an annotation tool to speed the process. We also conducted an Inter-Rater Reliability study to measure the agreement. Various linguistic, psychological and Twitter-based features are explored in conjunction with distinctive machine learning algorithms to develop psychological need models based on the conceptual layered reference model. These include 1) the Need Content Recognition (NCR) model, which is used to recognize need content, 2) the Need Type Identification (NTI) model, to identify the need type, 3) the Need Satisfaction Level Measurement (NSM) model, which measures individual need satisfaction level or whether the detected need is satisfied or frustrated, 4) the Social Context Evaluation (SCE) model to evaluate the individual surrounding environment and whether they are supportive or non-supportive, and, 5) the Life Aspect Identification (LAI) model which is employed to identify the life domain. Furthermore, the Frustrated Need Intensity Estimator (FNIE) model and Satisfied Need Intensity Estimator (SNIE) model are implemented within the third layer to obtain the intensity score of the satisfaction level. The results of our experiments affirm the effectiveness of the proposed framework and the developed psychological needs models. We implemented a prototype of the proposed framework in a real-life case study setting, analyzing population needs during two critical events: the Florida school shooting occurred on February 14$^{\text{th}}$, 2018 and the related March for Our Lives event which followed on March 24$^{\text{th}}$, 2018, and the New Zealand terror attacks, which occurred on March 15$^{\text{th}}$, 2019. The analysis of these critical events gave a clear indication of the feasibility of applying the proposed framework and its effectiveness in detecting changes among public reaction in terms of their psychological needs based on event evolution and authority response. The proposed framework could potentially be employed in a variety other application such as marketing and need-based recommendation scenarios.

The motivation behind the proposed framework in this thesis was to shed the light on the importance of recognizing human needs, which feed their emotions, which, in turn, motivate their actions and behaviors. Our goal is to illustrate that a powerful tool such as the current version of the proposed framework presented in this thesis could be instrumental in deciphering the temperament of a population, and open new avenues for improvement in determining more effective solutions, especially in critical situations. Based on the research conducted in this thesis, we did discover some limitations of the current version of the framework that we will highlight below. Then, we will also accentuate possible extensions of the framework, and several interesting future directions which could be investigated further.

7.2 Limitations

- A major drawback of any social media analytic research is the availability of data [64]. Data tagged with spatial and temporal information is essential to successfully analyze critical events within our framework. Therefore, to have a valid representation of the total population in spatiotemporal analyses, an adequate amount of data is required.

- The current version of the framework measures the overall satisfaction level of a given text in layer 1.2. In some cases, a given text might include mixed feelings and emotions towards more than one aspect being evaluated. Resolving the issue of these mixed emotions could increase the overall success rate of layer 1.2, by inferring a more accurate and specific satisfaction level. Adapting the aspect-sentiment technique, which aims to identify which sentiment is expressed towards which specific feature or aspect, is a potential solution to this issue.

7.3 Future Directions

- Our constructed dataset considered the three basic psychological needs, based on SDT, in layer 1.1. Enriching this layer with other psychological needs is a possible future expansion. This enhancement could provide a more comprehensive and representative psychological need dataset. Additionally, instead of expanding the psychological need dataset through manual labeling, which is a time-consuming and laborious task, an investigation into an appropriate method for automatic and accurate human need annotation is another possible line of research.

- The critical step of feature selection and extraction affects the performance of most classical machine learning algorithms. Therefore, in this work we explored the effectiveness of various hand-coded features, which we selected after consulting a domain expert, in detecting psychological needs. We then reported on their effect both individually and in combination. After expanding the dataset, the next step is to use deep learning algorithms to conduct an automatic feature extraction directly from the raw data. These algorithms have the ability to extract a wide range of high-level features without requiring any feature engineering.

- The current framework only considered the textual data in determining psychological needs. Other social media content, including links, images and videos, could provide more valuable information and is worth exploring. A classification approach in deducing individual psychological needs from images and videos is a new direction that should also be explored for future research.

- Classifying short text into one of the nine life aspects is still a challenging task. Extensive investigations into better handling this obstacle in order to improve the classification model accuracy would be beneficial. Employing semantic knowledge using Name Entity Recognition (NER) combined with knowledge-based techniques could present a possible solution that might result in a more accurate life aspects classification [99]. NER extracts information to identify the named entities within text such as names of persons, organizations, locations. Knowledge based techniques identify the extracted information and reveals the ambiguity from data sources such as DBpedia[1]. This would resolve the issue of classifying social media short text that includes names and links into the most appropriate life aspect category.

- Another direction for future work to be considered could entail extending the capability of the framework by integrating multilingual aspects for needs analysis in other commonly spoken languages to cover a wide range of geographical locations.

- Summarizing the causes of the satisfied and frustrated need experience could represent another valuable improvement in helping to discover deeper insights from the data. This could help by presenting the result of need recognition in a more interpretable way, where the identified need and the measures satisfaction level would be aligned with the causes. Currently, we use an abstract summarization method, a Term Frequency-based summarization, to detect the causes of need experience through identifying the active-sub topic in the form of associated hashtags within the main event hashtags, and the most frequent words used (stop words were excluded) in order to understand the theme of the discussion [74]. Creating a descriptive summary for each sub-topic is needed to provide both aspect coverage and viewpoints preservation.

[1]https://wiki.dbpedia.org/

Appendix A

Layer 1: Need Content Recognition (NCR) Model

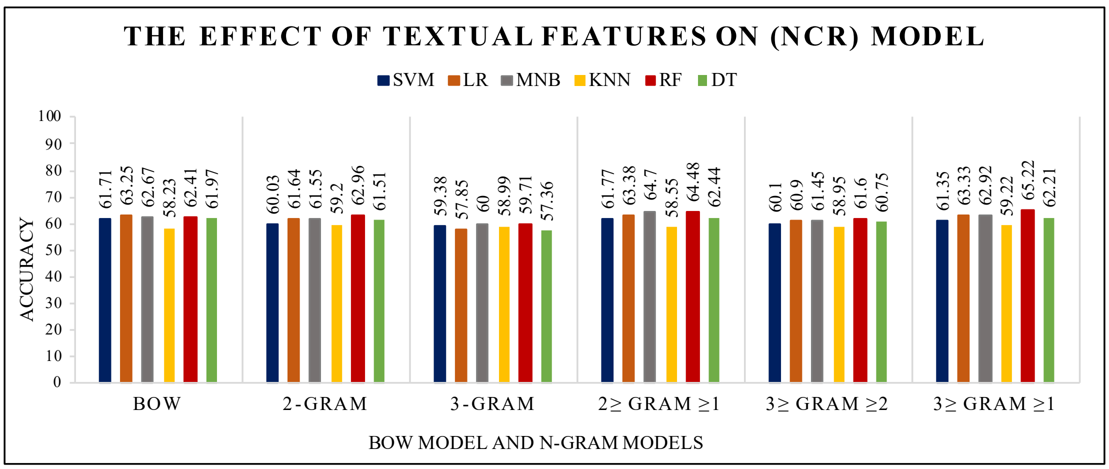


Figure A.1: The effect of different textual features on the accuracies of NRC model.

Table A.1: F-score and accuracy of Need Content Recognition (NCR) Model using different features for psychological needs dataset without emotional hashtags.

	SVM		MNB		LR		KNN		RF		DT	
Features	A%	F	A%	F	A%	F	A%	F	A%	F	A%	F
LIWC	65.03	0.65	60.76	0.51	66.81	0.65	56.60	0.566	65.95	0.64	57.29	0.57
LIWC + Emojis	65.25	0.65	59.38	0.48	64.59	0.63	56.38	0.56	64.44	0.62	60.1	0.59
LIWC +3≥gram≥1+ Emoji + Emotion Word Embeddings (EWE)	62.32	0.62	64.99	0.64	64.59	0.62	55.74	0.54	62.99	0.58	59.93	0.59

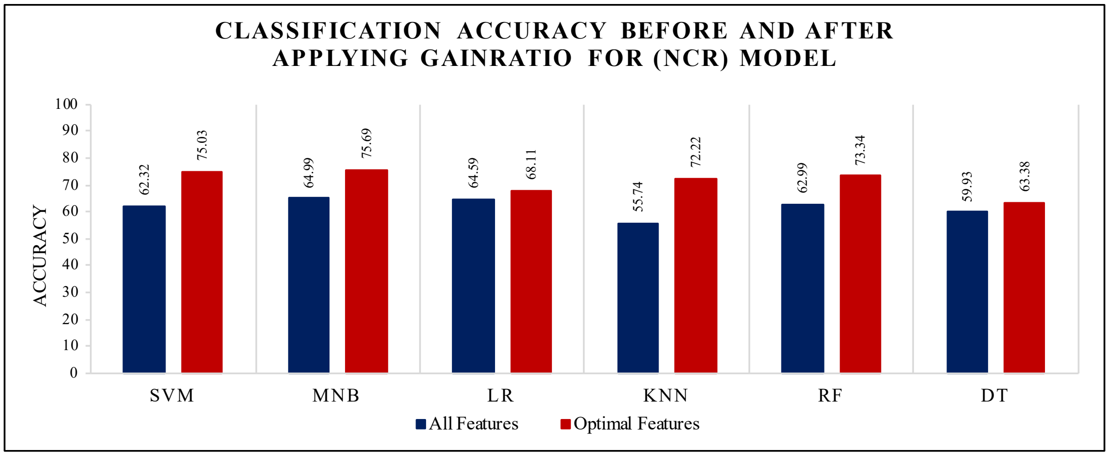


Figure A.2: NRC model accuracy before and after selecting the most predictive features using GainRatio.

Layer 1.1: Need Type Identification (NTI) Model

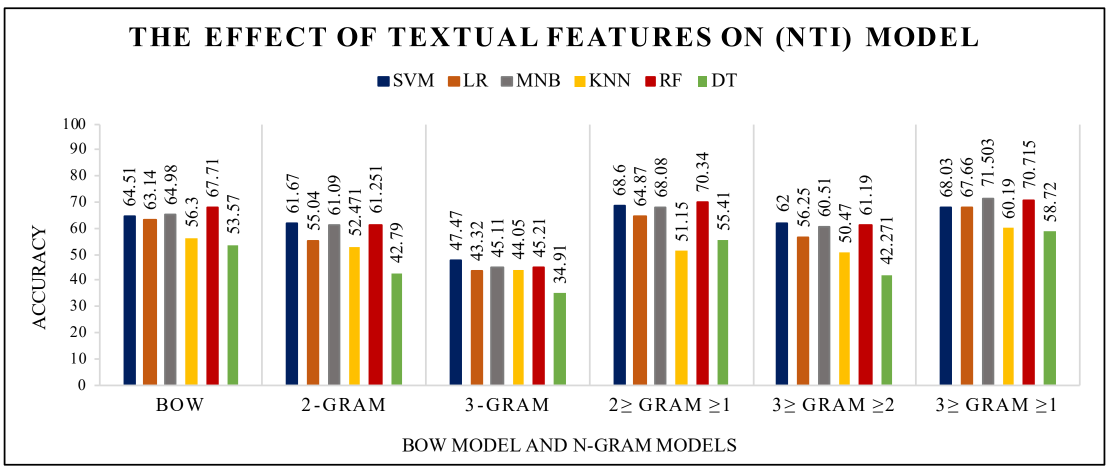


Figure A.3: The effect of different textual features on the accuracies of NTI model.

Table A.2: F-score and accuracy of Identifying Need Type (INT) model using different features for psychological needs dataset without emotional hashtags.

	SVM		MNB		LR		KNN		RF		DT	
Features	A%	F	A%	F	A%	F	A%	F	A%	F	A%	F
LIWC	64.72	0.64	59.98	0.59	64.19	0.64	61.19	0.60	69.55	0.69	56.309	0.56 \
LIWC + LCM (DAVs, IAV, SV)	65.77	0.65	60.09	0.60	64.66	0.64	65.35	0.64	70.03	0.69	57.25	0.57
LIWC + Emojis	64.30	0.64	59.56	0.59	64.09	0.64	66.351	0.65	71.08	0.70	56.30	0.56
LIWC + Emoji + LCM (DAVs, IAV, SV)	65.72	0.65	59.56	0.59	64.93	0.64	65.66	0.64	70.71	0.70	57.57	0.57
LIWC + Emoji + LCM (DAVs, IAV, SV + Categorized Emoji	65.77	0.65	60.19	0.60	65.29	0.65	66.56	0.65	71.08	0.70	56.99	0.57
LIWC + Emoji + LCM (DAVs, IAV, SV + Categorized Emoji + Colored Emoji	65.87	0.65	60.30	0.60	64.66	0.64	66.19	0.65	70.03	0.69	56.78	0.56
LIWC + 3≥gram≥1 + Emoji + LCM (DAVs, IAV, SV + Categorized Emoji + Colored Emoji	72.765	0.72	73.29	0.73	71.34	0.71	64.353	0.63	73.81	0.73	60.98	0.60\

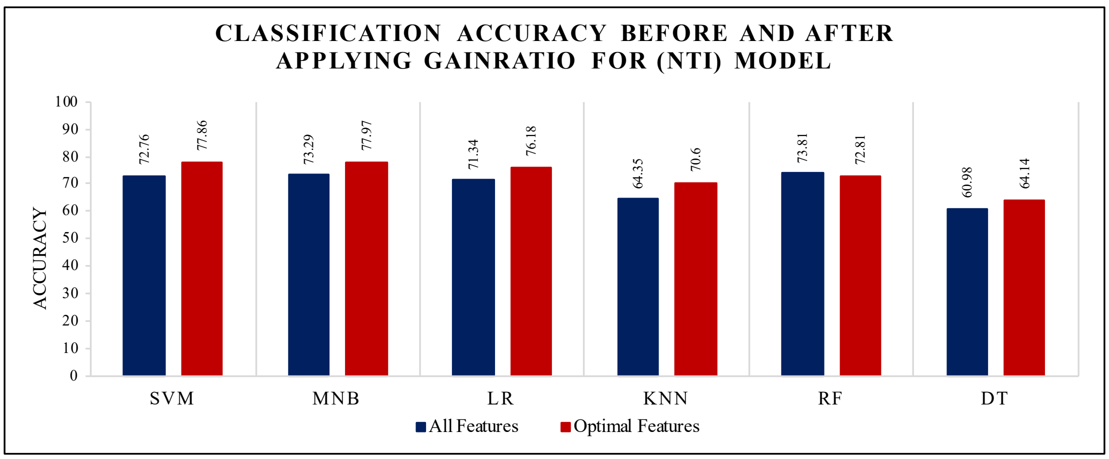


Figure A.4: NTI model accuracy before and after selecting the most predictive features using GainRatio.

Layer 1.2: Need Satisfaction Level Measurement (NSM) Model

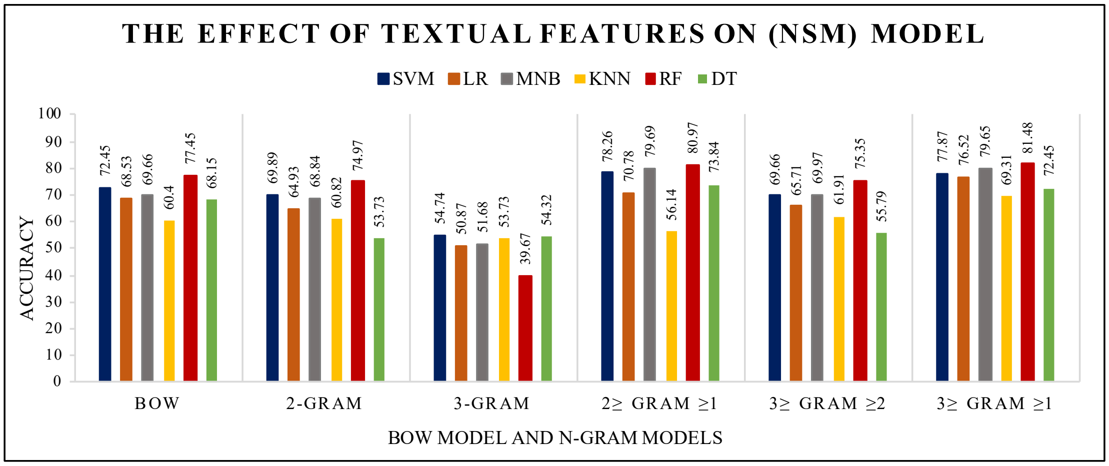


Figure A.5: The effect of different textual features on the accuracies of NSM model.

Table A.3: F-score and accuracy of Need Satisfaction Level Measurement (NSM) mode using different features for psychological needs dataset without emotional hashtags.

	SVM		MNB		LR		KNN		RF		DT	
Features	A%	F	A%	F	A%	F	A%	F	A%	F	A%	F
LIWC	59.12	0.585	53.19	0.50	58.27	0.57	66.56	0.65	80.04	0.80	67.84	0.67
LIWC + Emojis	59.04	0.58	53.15	0.50	58.34	0.57	66.44	0.64	80.162	0.80	67.76	0.67
LIWC + Emojis+ Sentiment Emojis	61.72	0.61	53.85	0.51	60.51	0.60	66.91	0.65	81.71	0.81	68.53	0.68
LIWC + Emojis+ Sentiment Emojis+ Categorized Emoji	62.03	0.61	54.74	0.52	61.44	0.61	66.64	0.65	82.13	0.82	69.27	0.69
LIWC + Emojis+ Sentiment Emojis + Categorized Emoji + Colored Emoji	62.14	0.61	54.78	0.52	61.41	0.61	66.40	0.64	82.21	0.823	68.84	0.68
LIWC + NRC+ Opinion Lexicons	60.13	0.59	54.04	0.51	60.20	0.59	66.36	0.64	81.01	0.81	66.79	0.66
LIWC + NRC + Opinion Lexicons + Emojis + Sentiment Emojis + Categorized Emoji + Colored Emoji	61.83	0.61	54.70	0.52	61.64	0.61	66.29	0.64	82.60	0.82	69.93	0.69
LIWC + 3≥gram≥1 + NRC + Opinion Lexicons + Emojis+ Sentiment Emojis + Categorized Emoji + Colored Emoji	81.24	0.80	81.01	0.80	80.78	0.80	65.16	0.632	83.80	0.83	74.19	0.74

Layer 1.3: Social Context Evaluation (SCE) Model

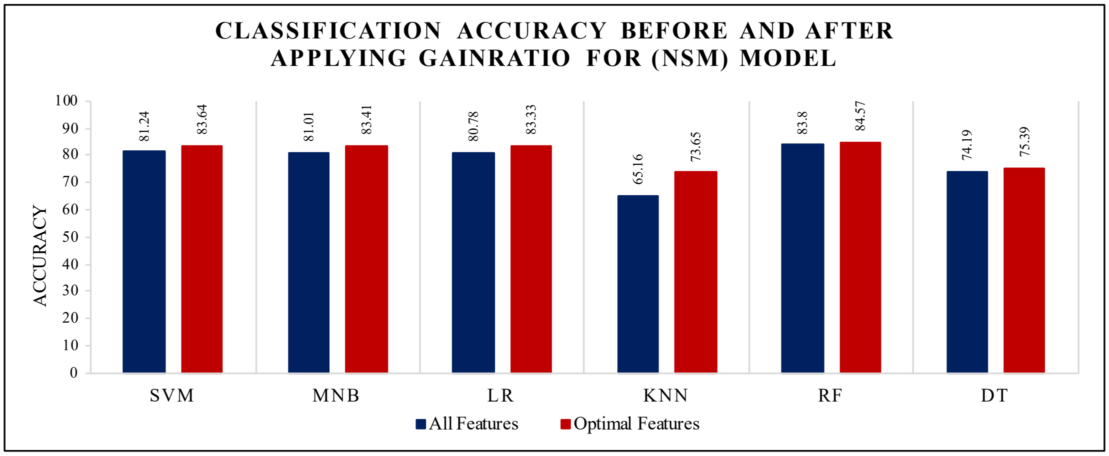


Figure A.6: NSM model accuracy before and after selecting the most predictive features using GainRatio.

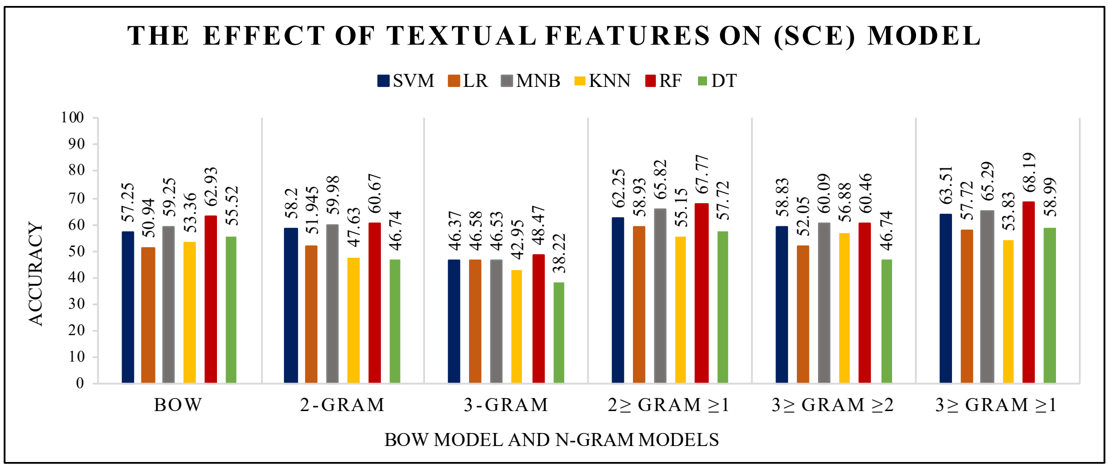


Figure A.7: The effect of different textual features on the accuracies of SCE model.

Layer 1.4: Life Aspect Identification (LAI) Model

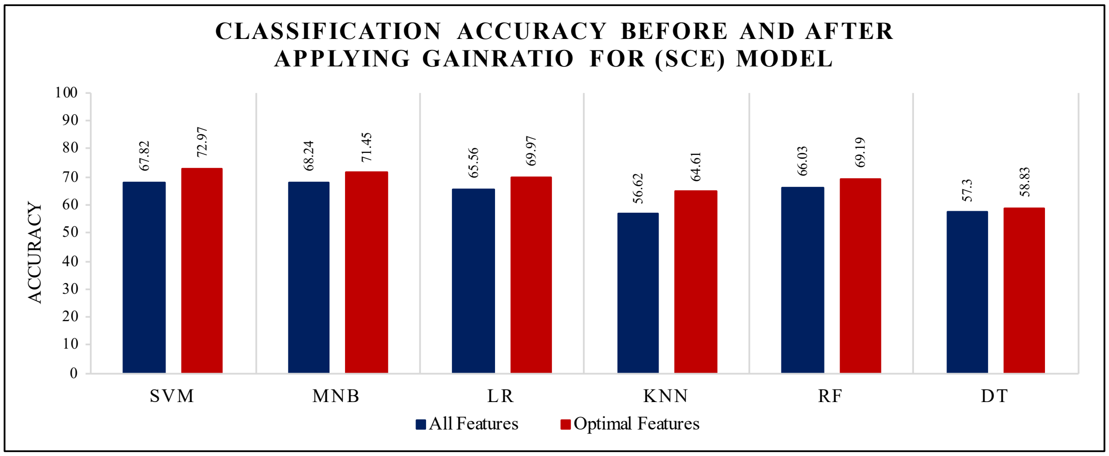


Figure A.8: SCE model accuracy before and after selecting the most predictive features using GainRatio.

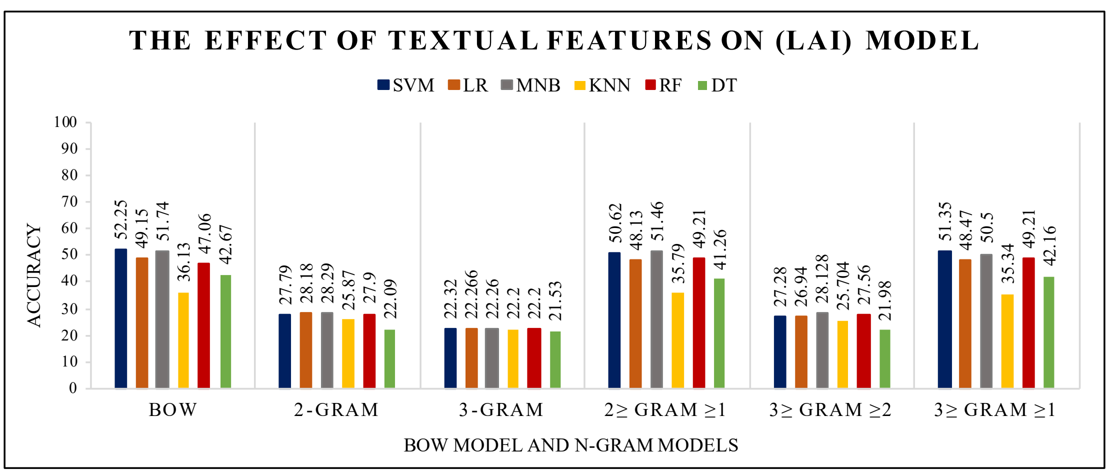


Figure A.9: The effect of different textual features on the accuracies of LAI model.

Table A.4: F-score and accuracy of Social Context Evaluation (ESC) model using different features for psychological needs dataset without emotional hashtags.

	SVM		MNB		LR		KNN		RF		DT	
Features	A%	F	A%	F	A%	F	A%	F	A%	F	A%	F
LIWC	57.99	0.57	57.72	0.57	58.25	0.58	59.41	0.57	67.13	0.67	54.41	0.54
LIWC + LCM (DAVs, IAV, SV)	58.20	0.58	56.99	0.57	58.25	0.58	59.09	0.56	67.03	0.67	55.20	0.55
LIWC + Emojis	58.04	0.58	57.67	0.57	58.25	0.58	59.35	0.57	66.82	0.66	54.36	0.54
NRC Word-Emotion	48.84	0.47	43.42	0.38	48.63	0.47	45.47	0.45	50.68	0.50	49.26	0.48
(MPQA, Bing Liu) Sentiment Lexicons + Sentiment Emojis	52.94	0.52	46.63	0.44	53.10	0.53	51.94	0.52	57.57	0.57	57.20	0.57
NRC Word-Emotion + (MPQA, Bing Liu) Sentiment Lexicons	55.20	0.55	51.15	0.50	55.41	0.55	50.89	0.50	57.46	0.57	51.73	0.51
LIWC + (MPQA, Bing Liu) Sentiment Lexicons + Sentiment Emojis	60.51	0.60	57.88	0.57	61.51	0.61	58.30	0.56	67.77	0.67	56.25	0.56
LIWC + NRC Word-Emotion	60.67	0.60	59.20	0.59	60.88	0.60	60.25	0.58	66.66	0.66	55.73	0.55
LIWC + NRC Word-Emotion + (MPQA, Bing Liu) Sentiment Lexicons	61.61	0.61	58.09	0.58	60.88	0.60	58.99	0.56	69.03	0.69	59.83	0.59
LIWC + NRC Word-Emotion + (MPQA, Bing Liu) Sentiment Lexicons + Emojis+ Sentiment Emojis	62.67	0.62	58.72	0.58	62.14	0.62	59.04	0.56	68.24	0.68	0.62	0.57
LIWC + 3≥gram≥1	67.24	0.66	68.45	0.67	62.93	0.62	49.42	0.44	71.45	0.71	56.62	0.56
LIWC + LCM (DAVs, IAV, SV) + 3≥gram≥1	67.19	0.66	68.50	0.67	61.93	0.61	49.57	0.44	70.50	0.70	56.57	0.56
LIWC + 3≥gram≥1 + NRC Word-Emotion	70.66	0.70	72.02	0.71	69.13	0.68	59.41	0.56	74.55	0.74	63.82	0.63
LIWC + 3≥gram≥1 + NRC Word-Emotion + (MPQA, Bing Liu) Sentiment Lexicons	67.56	0.66	69.08	0.68	50.21	0.45	65.66	0.65	69.97	0.70	58.25	0.58
LIWC + 3≥gram≥1 + NRC Word-Emotion + (MPQA, Bing Liu) Sentiment Lexicons + Emojis+ Sentiment Emojis	67.61	0.67	69.190	0.68	61.98	0.62	50.15	0.45	70.87	0.71	59.25	0.59
LIWC + 3≥gram≥1 + NRC Word-Emotion + (MPQA, Bing Liu) Sentiment Lexicons + Emojis+ Sentiment Emojis+ POS	65.82	0.65	68.24	0.67	64.56	0.64	51.05	0.46	69.24	0.69	60.19	0.60
LIWC + LCM (DAVs, IAV, SV) + 3≥gram≥1 + NRC Word-Emotion + (MPQA, Bing Liu) Sentiment Lexicons + Emojis+ Sentiment Emojis + POS + Emotion Word Embeddings(EWE)	67.82	0.67	68.24	0.68	65.56	0.65	56.62	0.53	66.03	0.66	57.30	0.57

Table A.5: F-score and accuracy of Life Aspect Identification (LAI) model using different features for psychological needs dataset without emotional hashtags.

	SVM		MNB		LR		KNN		RF		DT	
Features	A%	F	A%	F	A%	F	A%	F	A%	F	A%	F
LIWC	50.16	0.46	35.85	0.28	48.30	0.46	34.44	0.32	50	0.47	0.64	0.40
LIWC + Life Aspect Lexicons	52.25	0.49	39.85	0.337	51.40	0.49	35.0	0.33	52.87	0.49	42.22	0.41
3≥gram≥1 + LIWC	51.86	0.51	52.81	0.50	53.38	0.52	38.38	0.36	51.46	0.47	46.22	0.45
3≥gram≥1 + Life Aspect Lexicons	52.53	0.52	54.28	0.52	52.254	0.51	39.00	0.38	51.97	0.50	44.250	0.43
3≥gram≥1 + LIWC + Life Aspect Lexicons	51.80	0.51	53.04	0.50	54.00	0.53	38.83	0.36	52.48	0.48	46.95	0.461

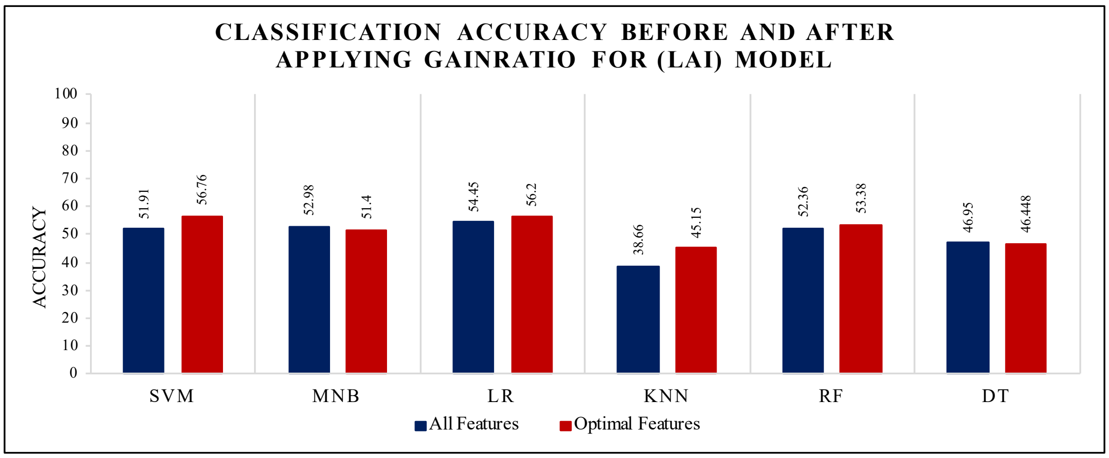


Figure A.10: LAI model accuracy before and after selecting the most predictive features using GainRatio.

Table A.6: Accuracy, Recall, Precision and F_{score} for the final NCR, NTI, NSM, SCE and LAI models.

Psychological Need Recognition Models	Best Classifier	Accuracy %	Recall	Precision	F_{Score}
Need Content Recognition (NCR) Model	MNB	75.69	0.75	0.76	0.74
Need Type Identification (NTI) Model	MNB	77.97	0.78	0.78	0.78
Need Satisfaction level Measurement (NSM) Model	RF	84.57	0.84	0.85	0.84
Social Context Evaluation (SCE) Model	RF	74.55	0.74	0.75	0.74
Life Aspect Identification (LAI) Model	SVM	56.76	0.56	0.56	0.56

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