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RESEARCH ARTICLE

Natural Language Processing (NLP) System for Cyberbullying Identification in Thai Language

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Abstract: In modern life, the easy access to the internet and social media has become almost essential. Although online social media channels are good means of communication, their frequency of cyberbullying and harassment creates problems as well. On these sites, cyberbullying takes many forms that cause targeted victims to experience anxiety, guilt, and despair. With an eye on demographic factors and personal experiences of victimizing, this study explores the degree and impressions of cyberbullying within a Thai sample community. By means of a thorough questionnaire survey, important new perspectives on respondents' awareness of cyberbullying, its underlying causes, and coping mechanisms for such events were obtained. Analyzing demographic data in tandem with cyberbullying experiences found a clear correlation between social media use length and the likelihood of running into cyberbullying. Moreover, the work suggests the creation of a customized natural language processing system specifically designed to identify Thai language cyberbullying events, therefore attaining an interesting accuracy rate of 84.23%. The study also points out the possible market chances for commercializing this method, implying it may be a profitable investment. These results provide a fresh understanding of language processing strategies for efficient content analysis on several internet platforms.

Keywords: cyberbullying detection, NLP-driven detection, social media identification, Thai language analysis, machine learning classification, linguistic analysis

1. Introduction

The fast advancement of technology and the great usage of internet applications, especially social networks define the present era. This shift has profoundly transformed communication and made efficient processing of big amounts of data necessary to maximize organizational operations [1, 2]. From traditional to more affordable methods, digital communication has helped media platforms—from conventional to more economical approaches—expanding to platforms like Facebook Live, YouTube, and Twitter (X) have transformed how people receive and exchange knowledge [3−7]. Along with these benefits, social media also has bad ones, most notably cyberbullying.

Cyberbullying takes the following many forms: text harassment, dissemination of damaging information, and distribution of fake news to inspire fanaticism or slander [8, 9]. As this information is shared online, it usually becomes ubiquitous and causes major uncertainty and disturbance. Cyberbullying is a worldwide problem with major repercussions for people and society that transcends any one area [10−12].

Although social media is a necessary tool for daily life in Thailand, it also provides a forum for cyberbullying, especially among teenagers where shockingly high victimization has been documented [13−15]. Beyond the impacted people, the consequences harm society welfare and put financial burden on governments and families [16]. Dealing with this problem calls for all-encompassing responses including raising awareness, creating efficient detecting techniques, and putting preventative action [13, 17].

Combining linguistics, computer science, and artificial intelligence, this work intends to solve cyberbullying in Thailand by means of tools for recognizing and evaluating occurrences of cyberbullying in the Thai language using natural language processing (NLP). Using NLP techniques, the paper investigates the complex dynamics of cyberbullying, identifies its underlying causes and manifestations and offers doable remedies to lower its frequency.

By means of an NLP-driven tool designed for the Thai language, this study provides unique insights on the demographic features and victimizing experiences related with cyberbullying. It aims to build a safer and more inclusive online world by offering practical methods to recognize and handle cyberbullying occurrences, therefore connecting technical improvements with social well-being.

1.1. Research contributions

The main contributions of the research are listed here:

1) The ideas of innovation, demography, social media, cyberbullying, and NLP are thoroughly analyzed in this work. It offers an extensive analysis of the evolution and use of technological solutions for social issues like cyberbullying.
2) Emphasizing the need to include various user characteristics in NLP models for recognizing cyberbullying, the research examines demographic factors like gender, age, generation, education, income, and occupation.

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3) The paper offers a thorough review of cyberbullying along with definitions, causes, many forms, and frequency in Thai surroundings. This knowledge helps developing suitable NLP solutions meant to identify and lower cyberbullying.
4) The paper suggests a novel NLP-based method intended to identify Thai language cyberbullying events. The system's accuracy degree came out as 84.23%. The results provide lawmakers, teachers, and technology developers withuseful statistics to enable them to effectively handle cyberbullying problems.

2. Literature Review

This section looks into the related problems of NLP, social media, and cyberbullying from the Thai language perspective. We have discussed several important essential concerns like the complex problem of cyberbullying, demographic elements affecting social media use, and innovation theory.

As defined, innovation is original ideas, behaviors, or products seen as novel. It offers innovative solutions for challenges [18]. In competitive environments, product innovation—with an eye toward effectiveness, variation, quality, and cost—is essential [19]. Process innovation, which aims at raising corporate efficiency, employs new technologies and resources to drastically rethink processes [20]. With a focus toward economic value, service innovation combines both new and existing knowledge [21]. It seeks to provide special products, marketing methods, or organizational tools. The dynamics of innovation highlight its great importance in defining social development and economic settings.

Examining demographic traits and social media use helps one to evaluate the impact on many creative ideas [22]. For instance, the study of social media use and demographic traits offers a whole picture of how creative ideas are adopted and accepted across several groups [22, 23]. Strategic decision-making is informed by such a study, which also makes it possible to implement focused strategies maximizing the relevance and effect of innovations within certain demographic sectors. Among the key determinants of behavior include gender, age, generation, education, money, and profession [24]. Men and women see and ideal differently; women are more vulnerable to outside influences [25]. Media consumption varies with age as younger individuals are more driven to idealistic ideals while older people favor practical uses [26]. Generation differences produce a range of ideas, beliefs, and attitudes among many age groups [27, 28]. Morals and cognitive processes are strongly influenced by education [29]. Socio-economic factors like income and job affect people's buying behavior; those with greater incomes place more value on quality and brand image [30].

Current demographic trends [31, 32] are largely influenced by social media channels and influencer dynamics. They provide many ways of interaction so that users of different backgrounds may participate actively and have conversations in both directions [33]. Users may also help by producing and distributing their own work, therefore altering the way demographics contribute to shape online stories. Often with large followings and the power to change ideas, tastes, and buying choices among their audience, influencers play a vital part in forming trends and influencing behaviors [34, 35]. One communication tool that allows participatory dialogues and user-generated content sharing is social media [36]. The numerous formats of the platforms help to link people and turn material users into content providers [37]. Offering a great variety of options for individuals and companies, social media has changed significantly and become a powerful instrument for communication, engagement, and content production [38, 39]. The extensive use of social media has resulted in the development of various issues connected to cyberbullying, which is now a major worry [40, 41].

Cyberbullying is a sort of bullying [8, 13, 17] wherein one deliberately uses information and communication technology to harm others. Cyberbullying could cause greater harm than more traditional kinds of bullying [15, 42]. Cyberbullying consists of actions including publishing embarrassing photographs or videos, sending threatening messages, and making negative comments on social networking sites [43]. Children and teenagers who may not yet have fully formed emotional and cognitive control systems [44] are its primary targets. Studies of teenagers reveal that a sizable fraction participate in cyberbullying—either as targets, offenders, or bystanders [14, 17]. Cyberbullying is caused in part by anonymity, convenience, emotional swings, and expressions, as well as by prejudice against others [15, 42]. Cyberbullying takes many different forms, including verbal abuse, sexual misbehavior, identity theft, and the creation of groups meant to attack people [11, 43, 44]. Direct cyberbullying, in which the bully interacts directly with the victim, and indirect cyberbullying, in which the attacker publicly posts negative material about the victim on social media sites [8, 13, 17, 45] are possible two classification of cyberbullying.

Common among young people in Thailand, cyberbullying typically shows up as harassment and invasion of privacy [14, 15]. According to the National Institute for Child and Family Development's 2019 study, Thai youngsters come across high degrees of endangerment, dishonesty, and harassment in both online and in-person learning environments. Thai youngsters usually see cyberbullying as normal or fun and use social media to communicate their emotions, which can lead to the spread of radical and extreme speech [46]. A major issue in Thailand, cyberbullying might have severe consequences like criminal activity and suicide [47]. A serious problem affecting most individuals, particularly children and teenagers, cyberbullying has significant effects on their mental and emotional wellness. The development of effective strategies to prevent and handle cyberbullying depends on understanding its causes and expressions.

Many researchers [48–51] have recommended the use of NLP, which entails the automated analysis and interpretation of human language, to address the growing worries about cyberbullying. From marketing to sentiment analysis to numerous business sectors [52, 53], NLP finds use in a broad spectrum. These uses often call for Python and the Natural Language Toolkit (NLTK [52]). NLP uses the random forest and decision tree algorithms for data mining and categorization among other purposes. Studies by Assegie and Nair [54] as well as Taha Jijo and Abdulazeez [55] have found them helpful for tasks like handwritten digit classification. Classification of data based on specific words depends on the probabilistic Naive Bayes Technique [56, 57]. Models are fully analyzed using evaluation criteria including accuracy, recall, and F-measure. In NLP applications, cross-validation is a frequently used method for choosing models and guaranteeing their robustness [58, 59].

All things considered; social media provide a channel of communication that lets one person reach a big audience. Because social media sites are so widely used in Thailand, cyberbullying is very common there. It appears in communications, material, pictures, and bogus news among other forms. Individuals supporting like-minded beliefs, denouncing, gossiping, slandering, and convincing others to interact with and post such material on social media [14, 44, 60] might mistakenly as well as deliberately contribute to this. Cyberbullying behaviors may quickly spread throughout the general population and lead to a broad trend of constant consuming and propagation, thus confusing [8, 16]. Conducting fresh research aiming to provide a thorough knowledge of the features, causes, relevance, and surroundings of cyberbullying can help one to grasp and address the growing occurrence of this phenomenon in Thailand. By means of NLP approaches, one may efficiently examine and assess the material, messages, and interactions on social networking sites. Furthermore, this study will be very important in developing a tool to spot cases of cyberbullying in Thailand and provide direction for the development of very effective instruments to assess cyberbullying.

3. Research Methodology

The research methodology is structured in accordance with the following methodical sequence, which aims to enhance comprehension of cyberbullying phenomena by utilizing NLP techniques to analyze content, communications, and interactions on social media platforms.

1) Data Exploration and Collection,
2) Attitudinal and Behavioral Survey,
3) NLP System Development, and
4) Exploration of Commercial Applications.

These steps contribute to understanding cyberbullying dynamics and offer practical solutions for combating cyberbullying within the Thai digital landscape.

3.1. Data exploration and collection

This stage entails collecting thorough information on cyberbullying, emphasizing in the Thai socio-cultural setting its drivers and trends. Data were gathered using a qualitative method by means of in-depth interviews with subject-matter experts from media, social sciences, and technology among other domains.

1) *Qualitative Research Methodology:* Comprehensive interviews were performed with specialists, encompassing university professors, executives from media organizations, a film director, a newspaper editor, representatives from the Thai Journalists Association, and researchers affiliated with the National Electronics and Computer Technology Centre. The purpose of these interviews was to clarify the conceptual framework, factors, and trends of cyberbullying in Thailand.
2) *Thematic Exploration:* The interviews focused on various manifestations of cyberbullying (e.g., verbal abuse, false information dissemination, and impersonation) and the online platforms where these activities occur. The potential for commercializing an NLP system for cyberbullying detection was also explored.

3.2. Attitudinal and behavioral survey

A systematic questionnaire (*Appendix*) was created to collect data on the attitudes and actions of Thai citizens about cyberbullying. The survey had four sections:

1) Part 1: Demographic Information—Collected data about respondents' gender, age, educational qualifications, and occupation.
2) Part 2: Knowledge and Perception of Cyberbullying—Evaluated respondents' comprehension and viewpoint of cyberbullying.
3) Part 3: Experience with Cyberbullying—Examined personal encounters or participation in cyberbullying situations.
4) Part 4: Preventive actions against Cyberbullying—Analyzed techniques and preventive actions utilized by people.

A sample of 100 respondents aged 15 to 40 years in Bangkok was calculated using Taro Yamane's technique. Data were gathered online using Google Forms and examined utilizing descriptive statistics (frequency, percentage, mean, and standard deviation). The reliability was assessed in a pilot study, yielding a Cronbach's alpha of 0.861.5.

3.3. NLP system development

This phase utilizes ideas from data analysis and surveys to create a NLP system designed to identify instances of cyberbullying in the Thai language.

1) Development Process: Data from social media networks were pre-processed by eliminating unnecessary symbols and segmenting Thai lexemes.
2) Model Proposition: A comprehensive model was developed to predict instances of cyberbullying, as delineated in Section 4.

3.4. Exploration of commercial applications

This phase assesses the viability of implementing the NLP system that has been developed for commercial purposes, including the potential for integration into existing platforms to improve online safety. A preparedness assessment for commercialization and a market feasibility analysis were implemented.

4. Implementation of Research Methodology

This section provides a detailed analysis of the implementation and results obtained from the systematic technique used in this investigation.

4.1. Interviews results on cyberbullying in Thailand

In-depth interviews were conducted with a total of eight experts and specialists in technology and social sciences, including a university lecturer from the Business Technology and Innovation Management Program, an executive from mass media firms, a film director, a newspaper editor, an executive from the Thai Journalists Association, and researchers from the National Electronics and Computer Technology Centre. The objective was to delineate the definition, determinants, and patterns of cyberbullying in Thailand, as well as to underscore the significance of NLP in identifying cyberbullying. Table 1 presents a summary of the findings from interviews with eight experts.

However, qualitative surveys were unable to delve into in-depth interviews with cyberbullying victims due to the necessity of approval from the Research Ethics Review Committee for Research Involving Human Subjects, coupled with time constraints that hindered data collection and research execution.

The interviewees indicated that cyberbullying is a purposeful use of language to defame, coerce, or propagate misinformation online, often grounded in society norms and cultural settings. Cyberbullying mostly affects high school students, requiring educational initiatives and legislative measures to successfully combat online abuse.

Establishing cyberbullying detection systems and promoting partnerships with mental health agencies were seen as essential measures to alleviate the detrimental effects of cyberbullying on individuals and society as a whole.

4.2. Survey results on the attitudes and behavior related to cyberbullying

The results from comprehensive interviews with professionals from several fields have enabled the creation of a questionnaire to

Table 1
Summary of the findings from interviews

Interviewee	Key insights
Interviewee 1	Emphasized Thai cultural aspects in communication and the need for education to identify cyberbullying.
Interviewee 2	Highlighted historical power dynamics and the role of education in mitigating cyberbullying.
Interviewee 3	Correlated cyberbullying emergence with technological and societal divisions.
Interviewee 4	Discussed cyberbullying prevalence in traditional media and advocated for educational interventions.
Interviewee 5	Stressed the need for linguistic analysis and legal frameworks to combat online harassment.
Interviewee 6	Emphasized media monitoring and responsible communication to counter cyberbullying.
Interviewee 7	Highlighted the vulnerability of high school students and advocated for collaboration with mental health services.
Interviewee 8	Discussed legal provisions for prosecuting cyberbullying and evidence-based approaches to combating it.

assess the attitudes and behaviors related to cyberbullying among Thai persons.

4.2.1. Quantitative results of the survey

This study evaluated the questionnaire's quality regarding its validity and reliability.

1) *Validity:* The content validity was assessed by three experts, yielding an item objective congruence (IOC) value of 0.92. Questions having an IOC score beyond 0.5 were included in the questionnaire.
2) *Reliability:* The questionnaire was tested with 30 individuals to verify its clarity and relevance. The reliability study with Cronbach's alpha coefficient produced a result of 0.861, signifying high dependability.

Questionnaires were administered to 119 persons, of whom 103 were considered pertinent for participation. The condensed findings are shown in Tables 2, 3, 4 and 5.

In summary, the questionnaire findings indicate that all respondents are aware of cyberbullying. Most perceive it as digital technology-based oppression, with many having experienced or witnessed it. There is widespread agreement on the necessity of preventive measures and interest in utilizing a cyberbullying identification system.

4.2.2. Testing the relationship

This section examines the correlation among pertinent variables using ANOVA analysis. The hypotheses were examined to investigate the correlation between demographic variables and cyberbullying.

1) H1: A correlation exists between gender and the observation of cyberbullying ($p = 0.832$; not significant).
2) H2: A correlation exists between age and the observation of cyberbullying ($p = 0.602$; not significant).
3) H3: A correlation exists between education and the observation of cyberbullying ($p = 0.975$; not significant).
4) H4: A correlation exists between the duration of social media use and the observation of cyberbullying ($p = 0.001$; significant).

In summary, gender, age, and education exhibit no substantial correlation with the observation of cyberbullying. Nonetheless, the duration of social media engagement is positively associated with the observation of cyberbullying. The findings support the creation of an NLP system to proficiently combat cyberbullying.

5. Proposed Model for Identifying Cyberbullying in the Thai Language

This section introduces the proposed model for identifying cyberbullying in the Thai language utilizing NLP techniques. The procedures involved in developing the NLP model for cyberbullying identification are depicted in Figure 1 below.

5.1. Data collection

Two main phases of data collecting were set in order to ensure complete understanding of the prevalence and dynamics of

Table 2
Part 1 demographic profile of respondents

S/N	Demographic characteristic	Frequency	Percentage
1.	Gender		
	- Male	42	40.78%
	- Female	41	39.81%
	-LGBTQIA+	20	19.42%
2.	Age	26-30 years old	27.20%
3.	Education	Bachelor's degree	61.30%
4.	Monthly Income	15,001-30,000 baht	38.80%
5.	Occupation	Private company	63.10%
6.	Social Network Used	Twitter	58.30%
7.	Time Spent on social media	3-5 hours/day	32.00%

Table 3
Part 2 knowledge, experience, and preventive measures

Aspect	Percentage
Awareness of Cyberbullying	100.00%
Understanding of Cyberbullying	48.50%
Main Cause of Cyberbullying (Anonymity)	50.50%
Influence of Social Structures	43.70%
Perception of Difference Between Traditional and Cyberbullying	40.80%

Table 4
Part 3 involvements or experience of being victimized by cyberbullying

Involvement/Experience	Percentage
Witnessing Cyberbullying	Ignored: 56.3% Commented: 24.3% Forwarded: 19.4%
Involvement in Cyberbullying	Ignored: 39.80% Sought Support: 16.50% Fought Back: 32.0%

Table 5
Part 4 preventions against cyberbullying

Involvement/Experience	Percentage
Agreement on Need for Preventive Measures	58.30%
Support for Cyberbullying Identification System	38.80%
Suitable Users for Cyberbullying Identification System	General Public: 43.70% Educational Organizations: 41.70%
Interest in Using Cyberbullying Identification System	72.80%

cyberbullying in Thailand. There was both qualitative and quantitative data collection among the processes:

A. *Gathering of qualitative data*

This phase aimed to get thorough opinions from experts to define the conceptual framework of cyberbullying in the Thai environment. The process included the following:

1) Eight professionals from several fields—media executives, university professors, and researchers from the National Electronics and Computer Technology Centre (NECTEC)—were chosen to use a deliberate selection process.
2) Semi-structured interviews were undertaken with an eye on the following:
    1) Definitions and taxonomy of cyberbullying.
    2) Platforms where cyberbullying is quite common.
    3) Factors of society and culture affecting cyberbullying in Thailand.
    4) Evaluation of NLP technology feasibility and possible applications for cyberbullying detection.
3) Interviews were done online, using Google Meet or Zoom, as well as in person. Every session was recorded under participant consent, transcribed, and theme analyzed

B. *Gathering of quantitative data*

This phase sought to use survey methods to measure cyberbullying incidence and perspective:

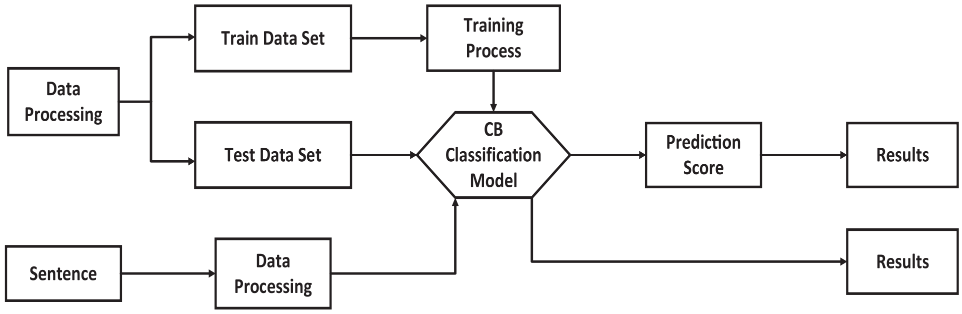
1) Survey design: Four components comprised the created structured questionnaire:
    1) Gender, age, education, and employment comprise demographic information.
    2) Knowledge and Views on Cyberbullying: Respondents' opinions and knowledge about this phenomenon.
    3) Personal experience with cyberbullying: Direct or indirectly encountered.
    4) Methods of prevention: Techniques meant to stop or reduce cyberbullying.
2) *Selection of sample:* Emphasising Bangkok's social media users, a sample of one hundred respondents between the ages of fifteen and forty was selected. With a 95% confidence level, Taro Yamane's formula lets one ascertain the sample size.
3) *Platform for gathering data:* Google Forms was the online survey tool used for data collecting. Respondents came from academic networks and social media sites.
4) *Validation of data:* Thirty individuals in pilot research were used to guarantee the validity and clarity of the questionnaire, therefore producing a Cronbach's Alpha of 0.861.

C. *Social media data gathering:*

A corpus of social media data gathered from publicly accessible Twitter material was assembled to build and teach the NLP model:

1) Data Source and Timeframe: Tweets gathered during two weeks (July 1–15, 2021). Twitter was chosen because of its popularity

Figure 1
Procedures for developing natural language processing



among Thai users and the great chance of cyberbullying material presented in its short-message style.
2) The Twitter API was used to gather tweets using certain terms and hashtags linked with cyberbullying (e.g., "bully," "harass," and their Thai counterparts).
3) Preprocessing included emoji elimination, misspellings corrected, and segmentation using Pythai-newmm for Thai language processing.

5.2. Data screening

Data collected from social media sites underwent a thorough screening procedure to guarantee the relevance and correctness of the dataset for training the NLP model. The following standards were followed:

1) Content Relevance in Language*:* The dataset consisted only of tweets composed in the Thai language. Content in other languages was filtered out using a language filter therefore maintaining the linguistic coherence of the dataset. Particularly intended to grab pertinent material were tweets using cyberbullying-related terms or hashtags. These keywords came from past meetings with subject-matter experts and current Thai cyberbullying research.
2) Ignoring Incomplete or Irrelevant Information:
    1) Tweets mostly include photos, videos, or links without accompanying text were deleted as the NLP model cannot handle them.
    2) Retweets and duplicate entries were screened out to have a varied dataset and prevent repetition.
    3) Tweets deemed spam, promotional material, or unrelated to the objective of the research were deleted to improve data quality.
3) Data on temporal filtering were gathered throughout a designated period (July 1–15, 2021) to provide a moment of cyberbullying activity during this period. This guaranteed the dataset was relevant to the present social media scene and temporally consistent.
4) Mild and severe cyberbullying incidents were included to help to balance the results. Tweets were classified according to their linguistic intensity and removing very gory or sensitive material. This is done to uphold ethical standards.

These screening criteria guaranteed that the dataset fit for creating a good NLP-based detection model and was typical of cyberbullying in the Thai environment.

5.3. Data preprocessing and cleansing

Comprehensive data preparation is crucial and time-consuming in natural language analysis and processing to guarantee consistency in the acquired data before model building or further research. The following steps define the methods of data cleansing used in our proposed model:

1) *Removal of emojis:* Here, the system will remove all emojis (emotional symbols) in the text message before processing it, since these emojis do not enhance the semantic substance of the text and neither do they facilitate the processing.
2) *Misspelt messages:* The system fixes misspelt words found during processing. Users could inadvertently misspell words or use too strong consonants to portray feelings. For example, the text message "ดีมากกกกกกกกกก," has too many consonant "ก," so the system can correct it by removing the redundant letter thus, maintaining the original meaning.
3) *Correction of orthographic errors arising from language shifts:* The method rectifies misspelt words that occur owing to transitions between languages, such as Thai to English. Texts often include mistakes because users neglect to change languages, requiring repair to maintain processing correctness.
4) *Redundant words:* Some Thai words that are repeated might be deleted without compromising the overall meaning of the work. Redundant words are found and eliminated to improve processing speed without sacrificing semantic integrity.

5.4. Feature engineering

By extracting significant insights from the text, feature engineering helped to greatly raise model accuracy:

1) *Lexical features:* A lexicon was developed by hand identification and use of words and phrases connected with cyberbullying. Each text was assessed in relation to these elements either present or absent.
2) *Word frequency:* This is used to calculate and used as input data, this lets the algorithm spot trends in cyberbullying language.
3) *Binary vectorization:* Texts were turned into binary feature vectors in which every vector element denoted the existence (1) or absence (0) of a certain word in the lexicon.

These technological aspects guaranteed that the model was ready to precisely identify cases of cyberbullying in Thai social media material.

5.5. Thai word segmentation

Analysing Thai text requires Thai word segmentation, an essential step for proper language processing. Subsequent to segmentation, the text may undergo more complex processing. This study assesses the NLP module of the proposed system, designed especially for segmenting Thai words while preserving their semantic integrity by using the Pythai-newmm algorithm in NLTK.

The processing capacity of the system was evaluated to gauge segmentation efficiency of Thai words. Different sentence counts 1, 10, 100, 1,000, and 10,000 were used to assess the segmentation technique. Table 6 shows the assessment results along with the processing times.

Table 6
Speed efficiency of Thai word segmentation by Pythai-newmm model

Number of texts	Number of words segmented	Time
1	23	5 seconds
10	216	6 seconds
100	2,250	24 seconds
1,000	21,987	3 minutes and 15 seconds
10,000	210,160	32 minutes and 5 seconds

5.6. Applied algorithms

The proposed NLP model is designed to distinguish text as either cyberbullying or non-cyberbullying using machine learning methods as follows:

1) *Naive Bayes classifier:* This classifier algorithm was selected for its easy-to-use nature and efficiency in text classification problems as this probabilistic method. It uses word frequencies to determine the probability that a text falls into a certain category.
2) *Decision tree algorithm:* Text categorization was developed using a structured approach derived from decision trees, which also helped to discover cyberbullying linguistic trends.
3) *Cross-validation:* Ten-fold cross-valuation was used in order to improve the model's resilience. This guaranteed the model was tested and verified throughout many data splits, hence lowering the overfitting risk.

5.7. Data training preparation

Model training necessitates a data lexicon that categorizes terms as indicative of cyberbullying or non-bullying conduct. This lexicon is based on tagged data from social media. The model is trained by categorizing words as either "bully" or "non-bully." Examples of categorized phrases are shown for clarification.

1) An example of "non-bully" sentences

```
<NonBully>สู้/1/NonBully/1/NonBully|ทุกทีม|ไทย|เชียร์
/1/NonBully|หมด|เอา|แชม|ป์|กลับมา|ไทย|ให้ได้|นะ|</NonBully>
```

Result: สู้ๆทุกทีมไทยเชียร์หมดเอาแชมป์กลับมาไทยให้ได้นะ (Go Thailand Team! We root for you. Bring back our championship.)

2) An example of "bully" sentences

```
<Bully>ยิ่ง/1/ Bully |อยู่/1/ Bully |ประเทศ/1/ Bully |ยิ่ง/1/ Bully
|ชิบหาย/1/ Bully |!|</ Bully >
```

Result: ยิ่งอยู่ประเทศยิ่งชิบหาย! (The longer you stay, the more damned this country becomes!)

After categorizing the texts, the words are segmented to represent the respective groups (bully and non-bully). The results are stored in text files for each category, denoted as follows:

1) **Bully.txt:** Contains x sentences.
2) **Non-Bully.txt:** Contains x sentences.

Tables 7 and 8 provide illustrative examples of both bully and non-bully language used on social media, aiding in the preparation and categorization of training data.

5.8. Data training

Creating a prediction model for a large dataset entails using machine learning principles, including pattern recognition. This technique involves examining the information and developing an automated analysis model, a subset of artificial intelligence (AI) based on the principle that computers may independently learn patterns from data and make judgments.

Machine learning has two main categories: supervised learning and unsupervised learning, both of which are extensively used in current research activities for data analysis. The model we propose uses a comparable methodology to predict forms of cyberbullying by creating a standardized dataset to train the computer in independently recognizing patterns. The effectiveness of the proposed model is assessed using the 10-fold cross-validation method on the testing dataset. Additionally, the model is enhanced by using diverse algorithms to get an ideal predictive framework.

Data categorization often uses a binary classification method, using a decision tree algorithm to categorize text into two potential outcomes: affirmative or negative.

The following stages delineate the process used in forecasting text categories:

Step 1: Import Lexical Data

The first stage is importing the dictionary data into a list format, as seen in the following example:

```
with codecs.open('dictionary/bully.txt', 'r', "utf-8") as f:
    lines = f.readlines()
bullyList = [e.strip() for e in lines]
del lines f.close()
```

Step 2: Perform Tag Classification

Each sentence is tagged with its corresponding classification, represented in the format [(sentence, classification)]. For example, [(ดีใจยิ่งกว่าถูกหวยได้ฉีดวัคซีน, Nonbully)].

```
NonbullyTag = ['Nonbully']*len(NonbullyList) #
Create 'pos' list equal to NonbullyList
BullyTag = ['Bully']*len(BullyList) # Create 'neg'
list equal to BullyList
```

Step 3: Combine Dataset Training

Datasets from each classification are amalgamated to form the training dataset.

```
trainSen = list(zip(NonbullyList, NonbullyTag)) +
list(zip(BullyList, BullyTag))
# Create pair of word and tag list + neutral tag
```

Step 4: Word Segmentation

Utilize PyThaiNLP for word segmentation and generate word vectors.

```
vocab = set(chain(*[word_tokenize(i[0].lower()) for i
in trainSen])) # Create SET datatype from trainSen
(*vocab as set datatype)
featurSet = [({i:(i in word_tokenize(sentence.lower()))
for i in vocab}, tag) for sentence, tag in trainSen] #
featurSet as list datatype
```

Step 5: Model Training

Train the modl using the decision tree algorithm.

Top of Form

```
classifier = nbc.train(featurSet)
```

5.9. Measuring model effectiveness

To assess the effectiveness of the model, classification accuracy is computed through supervised machine learning. The analysis outcome is evaluated for the NLP module to determine accuracy and effectiveness based on precision, recall, and F-Measure indicators.

Table 7
Examples of bully words on social media (meaning in English below)

ฆ่ายกโคตร Kill the whole family	คนอิสานขี้เกียจ Isan people are lazy.	พวกเสร่อ Dumbasses	คนอินเดียตัวโคตรเหม็น Indian people stink.
ตายยกครัว Wish the whole family die	คนอีสานกินหมา Isan people eat dog meat.	มารยาทซาม Ill-mannered	ร้องเหมือนควายถูกเชือด Moaning like cattle in a slaughterhouse
ขันที Eunuch	อยู่ไปก็หนักแผ่นดิน Burden of the land	สุนัขรับใช้ Lackey	พวกพม่ามาเต็มห้างฯ ไม่น่าเดินเลย Burmese people are all over the mall. This place is not nice for shopping.
จ้างวานฆ่า Hire to kill	อิก้านสมองพิการ Crackbrained	เกรียน Troll	เสียงเหมือนหมาเห่าใบตอง Sounds like a howling dog
อุ้มลงทะเล Drown in the sea	แม่งแดกหมารึเปล่าวะ Does he eat dog meat?	ไดโนเสาร์ Fossil	พวกนี้มารยาทแย่มาก Ill-mannered folks
ฆ่าโบกปูน Kill him and lay cement on his corpse.	เลียแข้ง เลียขา Ass-licking	อิข้าวนอกนา Bastard	คนใต้ไอ้พวกชอบประท้วง Southern people love protesting
ตบคว่ำ Smack	จกข้าวเหนียวดึงสติ Eat sticky rice and put yourself together	อิปลวก Coyote ugly	พวกไม่มีมารยาท Ill-mannered folks
กระทืบแม่ง Stomp him	ศูนย์กลางจักรวาล Centre of the universe	อิสำเพ็ง Woman of the street	พวกสัมภเวสี Stray ghosts

Table 8
Examples of non-bully words on social media (meaning in English below)

จัดการดี Good management	ต้องชนะ Must win	ธุรกิจ Business	ปกป้อง Protect
จัดการสถานการณ์ Manage the situation	ตอนนี้วางตัวเป็นกลาง Currently impartial	นั่งคุยกับเพื่อน Sitting and chatting with friends	ประตูหัวใจ Door to my heart
จัดกิจกรรมเย็น Hold the evening activities	ตื่นเต้นชิบหาย Super exciting	น่ารัก Cute	ประเทศเค้ามีสิทธิเลือกได้ They can choose in their country
จำนวนเงิน The amount of money	ถ้าการเมืองดี If politics is good	น่าสนใจ Interesting	เป็นคนที่เฉยกับการเมืองมาก Very politically neutral
แจกฟรี Free	แบบทุกวันนี้ Today	นี่แหละการเมือง This is politics	เปิดรับบริจาค Accepting donations
ได้ใจ Conceited	ทำประโยชน์ Helpful	แนวทางพัฒนา Development approach	เมื่อฉันแชร์เรื่องการเมือง When I share political information
ตรวจตรา Patrol	ที่ควรได้ Deserving	บนพิสูจน์จริง Prove true	เราไม่ยุ่งการเมือง I don’t get involved in politics.

5.9.1. Precision, recall, and F-Measure

Precision: Measures the proportion of correctly identified bully texts among all texts predicted as bully.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

Recall: Measures the proportion of correctly identified bully texts among all actual bully texts.

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

F-Measure: Harmonic mean of precision and recall, offering a balance between the two metrics.

$$F - Measure = \frac{2 \times (Precision \times Recall)}{Precision + Recall} \tag{3}$$

Where:

1) *TP (True Positive):* Texts containing bully words correctly predicted as bully.
2) *FP (False Positive):* Non-bully texts incorrectly predicted as bully.

3) *FN (False Negative):* Bully texts incorrectly predicted as non-bully.
4) *TN (True Negative):* Non-bully texts correctly predicted as non-bully.

5.9.2. Model testing process and interpretation

The model's efficacy was evaluated via the 10-fold cross-validation method. The dataset was partitioned into 10 equal segments for training and testing, with each segment used for testing once, culminating in ten assessment cycles as seen in Figure 2.

Table 9 displays the test results, illustrating the model's efficacy in detecting cyberbullying using measures like recall, precision, and F-measure for both bully and non-bully categories.

After testing the model with 56,140 sentences, it was found that the model achieved an overall accuracy of 84.23%. The precision, recall, and F-measure metrics revealed that the model effectively identified both bully and non-bully texts, with respective accuracies of 82.85% and 85.41%. These results affirm the model's capability in discerning cyberbullying content with a high degree of accuracy.

5.10. Analysis and discussion

This paper presents an NLP method specifically designed to identify Thai language cyberbullying events. Acting as a key mechanism, it efficiently filters interactions, information, and messages across social networking sites. Representing a major success in this sector, the analytical results provide a basis for the creation of further technologies aiming at spotting cyberbullying in Thai. With an excellent 84.23% accuracy rate, this study emphasizes the seriousness of cyberbullying problems and the effectiveness of the created model.

Beyond the classroom, this concept has ramifications for the social development as well as the business sectors. It has potential in projects meant to lower suicide rates by properly handling cyberbullying, therefore decreasing depression. Furthermore, it can help business interests by offering a strong instrument for future prevention and monitoring of cyberbullying events.

6. Feasibility Analysis for Commercialization

Integrating NLP to fight cyberbullying in the Thai language has interesting commercialization opportunities. Different NLP methods allow for various subjects, connections, and data analysis tools, thereby addressing different issues. Especially from the informal language used in online communication, sentiment analysis is clearly a necessary tool of NLP as it helps to extract emotions from messages. Though NLP tools are somewhat common, there is a clear market vacuum as no specialized service providers target cyberbullying detection in the Thai language.

6.1. Market research insights

According to market research, particularly among students who make up a large number of cyberbullying victims, cyberbullying mitigating techniques are clearly in demand in Thailand. The negative consequences of cyberbullying—including social consequences and mental health problems—emphasize how urgently strong preventative actions are needed. Furthermore, emphasized by secondary assessments are the wider influence of cyberbullying on society and the possibilities of NLP technology to solve this common problem. NLP technology may greatly contribute to society's welfare and minimize its negative consequences by enabling stakeholders to monitor and fight cyberbullying properly.

6.2. Market potential and segmentation

The growing market for Big Data and business analytics indicates an increasing need for data-driven insights and solutions across

Figure 2
Model testing divided into ten rounds of cross-validation tests

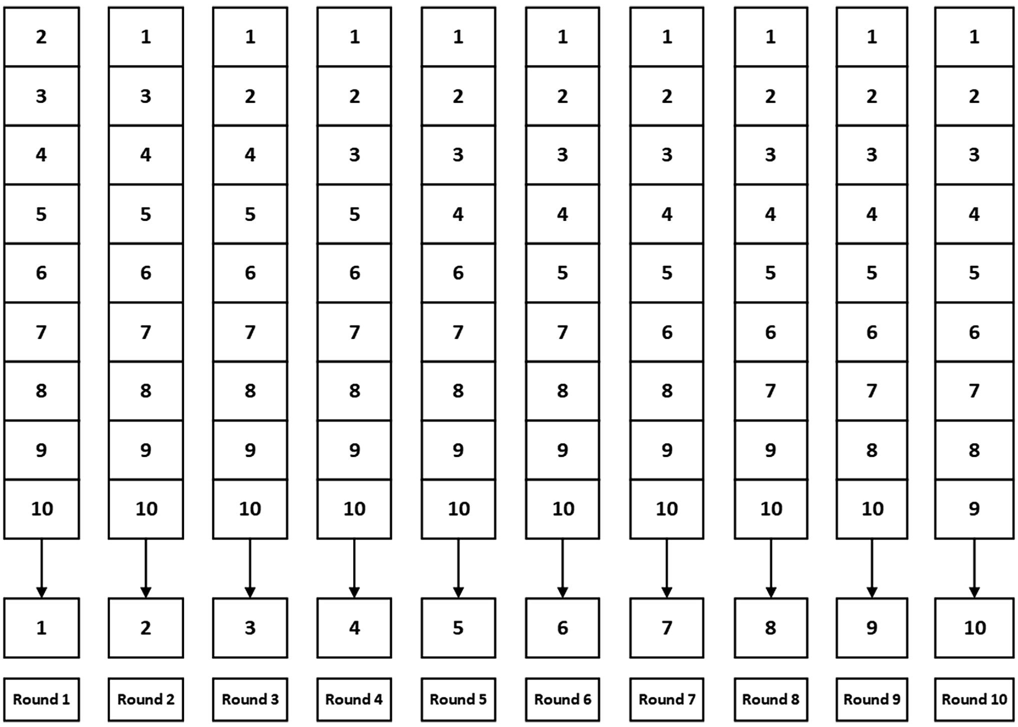


Table 9
Results of model effectiveness testing

Round	Bully			Non-Bully			Classifier Accuracy
	Recall	Precision	F-measure	Recall	Precision	F-measure	
1	0.7225	0.8810	0.7939	0.9025	0.7648	0.8279	0.8125
2	0.7475	0.92	0.8248	0.9350	0.7873	0.8548	0.8412
3	0.7775	0.9147	0.8405	0.9275	0.8065	0.8627	0.8525
4	0.7625	0.8970	0.8243	0.9125	0.7934	0.8488	0.8375
5	0.7975	0.9062	0.8484	0.91750	0.8191	0.8655	0.8575
6	0.78	0.8965	0.8342	0.9100	0.8053	0.8544	0.8450
7	0.755	0.9151	0.8273	0.93	0.7914	0.8551	0.8425
8	0.78	0.9043	0.8375	0.9175	0.8065	0.8584	0.8487
9	0.75	0.9091	0.82191	0.925	0.7872	0.8505	0.8375
10	0.7525	0.9318	0.8326	0.945	0.7924	0.8620	0.8487
Avg.	0.7625	0.90761	0.8285	0.9222	0.7954	0.8541	0.8423

diverse sectors in Thailand. Organizations are progressively emphasizing advanced analytical tools and automated procedures, using machine learning and artificial intelligence (AI) technology. The pervasive use of social media platforms in Thailand enhances the potential for NLP technology to effectively address cyberbullying. The market segmentation delineates government agencies, commercial firms, and other organiZations engaged in cyberbullying prevention and intervention initiatives. Customizing data detection and analytics services to address the distinct requirements of each segment guarantees relevance and efficacy.

6.3. Collaboration for impact

The pursuit of commercialization relies on collaboration with relevant stakeholders. Companies can raise awareness and effectively combat cyberbullying by collaborating with governmental entities, business groups, and other companies. Companies can present themselves as significant contributors to addressing this pressing societal issue by aligning their objectives and priorities with those of stakeholders.

6.4. Conclusive remarks

The feasibility study emphasizes the great financial possibility of using NLP technology for Thai language cyberbullying detection. By properly addressing cyberbullying via the increasing need for data analytics solutions and cooperation with pertinent stakeholders, companies may significantly influence society's welfare and thus contribute to economic success.

Moreover, the financial study shows how profitable it is to use the NLP system for business needs. The initiative will draw participants looking to benefit from Thailand's market's growing need for data analytics solutions because of its significant market potential, sensible capital expenditure, good profitability ratios, and expected revenue predictions.

7. Conclusion

The studies stress the general frequency and complex aspects of cyberbullying in Thailand as well as the effect of social systems, cultural surroundings, and digital platforms on the development of cyberbullying behavior. This work greatly advances society growth and economic prospects by creating a specific NLP system aimed to identify cyberbullying incidents in Thai language. With an accuracy score of 84.23%, the model was successful in spotting cyberbullying material and offered a basis for projects aimed to limit its psychological and societal consequences. Furthermore, examined in the research is the economic viability of the NLP technology and it is fit for integration into current monitoring and risk-reducing mechanisms. This study presents feasible technological options to solve this urgent social problem along with perceptive study of the subtleties of cyberbullying in Thailand.

Conceptual consequences: By combining NLP approaches with sociocultural research, this work advances our theoretical knowledge of cyberbullying. To find and handle cases of cyberbullying, the study shows the methodical investigation of language patterns—which are marked by cultural and demographic influences—in order to the findings add on the present corpus of information on the convergence of technology, language, and social behavior, therefore providing a basis for further research on automated detection systems in many sociolinguistic environments.

Managerial implications: From a management perspective, this research offers stakeholders— lawmakers, teachers, and technology developers among others—useable information. Developed in this study, the NLP model can potentially be operationalized as a surveillance tool in social media platforms, educational institutions, and companies to monitor and reduce cyberbullying incidence. Using this technology can help management in social media companies and educational contexts create safer online environments and enhance user experience, hence encouraging trust and engagement.

Limitations: This work is not free from restrictions even if it makes important contributions. This research focuses on the inhabitants of Bangkok, whose status as Thailand's capital and a cultural and economic center guarantees a certain level of variety in the sample. Bangkok hosts citizens from around the nation and expatriates from many professional and cultural backgrounds. We recognize that this variety does not completely reflect the whole of Thailand's population, and further research should strive to include individuals from more rural and regional areas to provide a more holistic view. Moreover, the reliance of the NLP system on publicly available data from social networking platforms can neglect encrypted or private conversations. The natural cultural uniqueness of the Thai language model limits its use in other linguistic or cultural setting.

Future research: This work uses NLP to provide the foundation for cyberbullying identification in Thai language, although it offers an opportunity for further research. To increase the generalizability of results, future studies shall focus on increasing the sample size and include people from many geographic, cultural, and socioeconomic backgrounds across Thailand. Furthermore, even although this study shows the efficacy of the proposed approach, future research is reserved for comparison studies with state-of-the-art models including those for multilingual or cross-cultural settings. Such analogies would let to benchmark the performance of the model and point out possible enhancements. Including multimedia content—such as photographs and videos—into the dataset might help the model be more resilient in practical settings. Moreover, creating multilingual NLP models would help to identify cyberbullying in many language and cultural environments, hence extending the relevance of the proposed approach. Future research shall also investigate techniques for analyzing encrypted or private messages while guaranteeing user privacy, handling material on cyberbullying that might not be publicly available. These guidelines will open the path for more thorough and scalable solutions meant to fight cyberbullying.

Recommendations

Following some of the suggestions below can assist to provide workable ideas for improving online surroundings and reducing cyberbullying:

Applying NLP-based monitoring tools: By including NLP-based monitoring technology, companies—especially social media platforms and educational institutions—could be able to quickly find and mark events of cyberbullying. Using this approach will help to stop the spread of negative content and provide quick fixes.

Support public awareness campaigns: Crucially, intensified public awareness campaigns informing consumers—especially younger groups—about the many forms, effects, and reporting strategies for cyberbullying events. Customizing these advertising tools to fit linguistic and cultural settings can help them to be more effective.

Create policies and legal frameworks: Policymakers have to improve already in-existing laws to properly address cyberbullying all around. This suggests the need of clearly defining the obligations of online platforms and applying strict legal actions for violators.

Promote stakeholder collaboration: Encourage stakeholder collaboration among government agencies, technology firms, educational institutions, and mental health professionals to formulate a unified strategy for addressing the issue of cyberbullying. This may include the establishment of victim assistance initiatives and the promotion of constructive online conduct.

Enhance innovation and research: Promote further investigations into the advancement of multilingual NLP models and the examination of novel data sources, such as multimedia information, to improve the precision and applicability of detection across various settings.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Bello Musa Yakubu: Conceptualization, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization, Funding acquisition. **Worapong Bumrungsri:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Pattarasinee Bhattarakosol:** Conceptualization, Methodology, Formal analysis, Resources, Data curation, Writing – review & editing, Supervision, Project administration, Funding acquisition.

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Appendix

Sample Questionnaire on Cyberbullying Awareness and Experiences
Part 1: Demographic Information

1. Gender
   i. Male
   ii. Female
   iii. Non-binary/Other (Specify: ___________)
2. Age
   i. Below 18
   ii. 18–25
   iii. 26–30
   iv. 31–40
   v. Above 40
3. Educational Qualification
   i. High School
   ii. Bachelor's Degree
   iii. Master's Degree
   iv. Doctorate
4. Occupation
   i. Student
   ii. Employed (Specify Industry: ___________)
   iii. Self-Employed
   iv. Unemployed
5. Monthly Income (if applicable)
   i. Less than 15,000 baht
   ii. 15,001–30,000 baht
   iii. 30,001–50,000 baht
   iv. Above 50,000 baht
6. Social Media Platforms Used (Select all that apply)
   i. Facebook
   ii. Twitter
   iii. Instagram
   iv. TikTok
   v. Others (Specify: ___________)
7. Time Spent on Social Media Daily
   i. Less than 1 hour
   ii. 1–3 hours
   iii. 3–5 hours
   iv. More than 5 hours

Part 2: Knowledge and Perception of Cyberbullying

   i. How familiar are you with the term "c"berbullying"?"Very familiar
   ii. Somewhat familiar
   iii. Not familiar

8. Which of the following do you think constitutes cyberbullying? (Select all that apply)
   i. Sending threatening messages
   ii. Spreading false information
   iii. Sharing private images without consent
   iv. Posting offensive comments
9. Do you think cyberbullying is different from traditional bullying?
   i. Yes
   ii. No
11. In your opinion, what is the primary cause of cyberbullying?
   i. Anonymity on social media
   ii. Lack of legal consequences
   iii. Social and cultural factors

Part 3: Experience with Cyberbullying

12. Have you ever been a victim of cyberbullying?
   i. Yes
   ii. No
13. If yes, what type of cyberbullying did you experience? (Select all that apply)
   i. Harassment through messages
   ii. Public shaming or humiliation
   iii. Identity theft or impersonation
14. How did you respond to the cyberbullying incident?
   i. Ignored it
   ii. Blocked the user(s)
   iii. Reported to the platform
   iv. Sought help from friends/family
15. Have you ever witnessed cyberbullying on social media?
   i. Yes
   ii. No
16. If yes, what was your reaction?
   i. Ignored it
   ii. Confronted the bully
   iii. Supported the victim
   iv. Reported it

Part 4: Preventive Actions Against Cyberbullying

17. Do you believe preventive measures against cyberbullying are necessary?
   i. Strongly agree
   ii. Agree
   iii. Neutral
   iv. Disagree
   v. Strongly disagree
18. Which of the following measures would you support to combat cyberbullying? (Select all that apply)
   i. Educational campaigns
   ii. Stricter laws and regulations
   iii. Advanced technological solutions (e.g., AI/NLP-based systems)
19. Would you be interested in using a cyberbullying detection system?
   i. Yes
   ii. No
20. Who do you think should have access to such systems?
   i. General public
   ii. Educational institutions
   iii. Law enforcement