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Visualizing Communication of Service Providers Reputation During Covid-19 Pandemic: A Conceptual Model

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ABSTRACT

This paper presents to fill the gap and proposes a new conceptual model in developing an application to visualizing the reputation of communication service providers (CSP) during the Covid-19 pandemic. The outbreak of the COVID-19 caused a significant increase in the usage of voice and data using CSP. Regardless of it is seems under a protective umbrella during the pandemic, the increasing demand for CSP in a pandemic may cause customers to switch for better service. CSP companies have an abundance of data about their customers; however, the social element mainly the pithy, real-time commentary express via networks such as Twitter is often overlooked. It is due to the widely used NPS (Net Promoter Score) to measure their customers' loyalty and satisfaction. Even some of the telecommunication has started venturing into social media data analytics, the improvements required in detecting the combination of many languages used in blogs and forums. This gap inclusive the short words, not enough sentiment analytics for non-English languages, and obviously, social media in non-English languages favoured comparing to English languages. Therefore, we proposed a comprehensive conceptual model that adapted from two existing conceptual models, Simulation in Modeling CM (2008) and Integrated Framework for CM (2016). We believed it could be a guideline in visualizing the reputation of CSP that involves extracting public tweets from twitter sentiment analysis. As a result, CSP companies can get a more unobstructed view of their reputation, insights about the products and services that their customers appreciate.

Key words: Communication service provider, Conceptual model, Covid-19, Sentiment analysis, Twitter

1. INTRODUCTION

Amid March of 2020, Malaysian Communications and Multimedia Commission (MCMC) observed that the demand for bandwidth has surged due to Malaysians currently staying at home following the implementation of the Movement Control Order (MCO) due to the outbreak of the Covid-19. Increased use of video conferencing, learning, shopping online, gaming, movie, and virtual meetings over the internet are making a higher demand for bandwidth inevitable. Adherence to the MCO by remaining indoors at all times saw 23.5% higher Internet traffic nationwide during the first week of the MCO, while the second week of the MCO saw a further increase of 8.6% [1]. Higher data consumption could create congestion causing speeds to fall and affected the user experience whereby longer loading time observed, particularly while consuming bandwidth-intensive content such as streaming services on High Definition (HD).

According to the report Mobile Experience during the Covid-19 pandemic: 4G Download Speed released by Opensignal, Malaysia's 4G download speeds dropped from 13.4Mbps on average in early February to an average of 8.8Mbps (March 23rd to March 29th, 2020). Similar trends also observed globally, where operators around the world are experiencing an unprecedented increase in bandwidth usage due to this behavioral shift [2]. Often operators are helping their users by offering extra mobile data for free, sometimes even offering unlimited data. It considers as a sign of the importance of mobile telecom during the crisis to both individuals and businesses—the trend of the 4G download speed decrease from January 27th until March 29th, 2020. There was an increase in data consumption, data limits on customers' mobile packages, location of mobile usage, hours of usage, and pre-emptive measures to reduce the risk of outages. As supported by [3] that the scenario is due to the increased use of video conferencing, learning, and shopping over the internet have made higher demand for bandwidth inevitable.

IBM Big Data & Analytics Hub stated that telecommunication companies have an abundance of data about their customers. Yet, the social element, particularly the concise, real-time commentary that consumers express via networks such as Twitter, is often overlooked. Twitter is a popular and famous micro-blogging service that able to track the public mood related to an object or entity and applying the sentiment analysis to extract sentiments conveyed by the users [4]. A lot of marketing executives are said not to comprehend how to integrate the power of the internet and social media into their marketing strategy.

Currently, CSP companies widely use NPS (Net Promoter Score) to measure their customers' loyalty and satisfaction [5]. NPS conjectured to be not precise enough to assess social media campaigns due to the method used is targeted only at existing subscribers, is based on the ultimate question. Another drawback of NPS its inability to provide context-specific insight and recommendations. It is just one question linked to business Key Performing Indicators (KPI) [6]. Hence, an individual's need at a particular moment in time is not taken into account by NPS metrics. Therefore, the NPS score obtained is regularly very generic and unrepresentative of variables.

Even though some CSP has started venturing into social media data analytics, but improvements reasonably required in detecting the combination of many languages used in blogs and forums, as well as short words. There is evidence of not enough sentiment analytics for non-English languages, and this research gap is becoming more apparent as social media in non-English languages gets more popular. Multilingual sentiment analysis is also vital for social sentiment analysis in multilingual societies [7].

Therefore, to solve the problem, this study explores the development of the conceptual model as a guide to have a better visualization of the CSP reputation in Malaysia during the Covid-19 pandemic based on twitter sentiment analysis. Anyone who uses the application can get the prompt and clear feedback on what user comments and expected from the CSP subscribed. Also, the proposed idea used another quantitative measurement to measure customers' satisfaction by using Net Brand Reputation (NBR) involves extracting public tweets from Twitter, which done using a Twitter scraping tool such as Twint. Sentiment analysis or opinion mining detects the sentiment from social media data and help CSP define policies and offer better services [8].

2. RELATED WORKS

In this section, we describe the Malaysian CSPs, reputation index, sentiment analysis, and visualization techniques as more in-depth knowledge on the related issue.

2.1 Malaysian Communication Service Providers

A communication service provider or CSP is a service provider that transports information electronically, as a telecommunications service provider. The term covers public and private companies in the telecom, internet, cable, satellite, and managed services businesses. Over the last 20 years, the telecommunication industry in Malaysia has gone through massive changes. Initially, there was only one service provider in the 1980s. Due to the government's liberalization policies, the number grew to seven by the mid-1990s [9]. Before the 1990s, the sector monopolized by Telekom Malaysia, which eventually rebranded to TM. Throughout the 1990s, additional licenses given to five other companies, which are Mobikom, Celcom, Maxis, Mutiara Swisscom, which is now called Digi, and Sapura Digital. The 20 years of revolution have then produced four industry players, which are Maxis, Celcom, Digi, and U Mobile [10].

Maxis Communications Berhad, or formerly known as Binariang, was established in 1993 by Ananda Krishnan. Maxis purchased Time Cel, an entity that existed after the merger of Sapura Digital and Time Wireless due to the 1997-1998 Asian financial crisis. Maxis categorized as a prospector due to its utilization of satellite technologies, which was made possible by its sister company. In terms of investing and improving its infrastructure, Maxis has generally been the most innovative company. Today, as communications converge more and more with multimedia, Maxis offers integrated communication and Internet-based solutions, through both fixed and mobile voice and data services [11].

Celcom started its operation as STM Cellular Communications in 1988 as a subsidiary of Syarikat Telekom Malaysia Berhad (STM). 51% of STM's share in the subsidiary company sold to Alpine Resources Sdn. Bhd. in 1989. After a year, the remaining 49% share in the company sold. Following this event, the company changed its name to Celcom Sdn. Bhd. [12]. Celcom is now a part of Axiata Group Berhad, one of the leading telecommunications groups in Asia. Axiata's website states that Axiata incorporated in Malaysia on June 12th, 1992, as a private limited company under the name of Telekom Malaysia International (TMI), which then operated as a division under Telekom Malaysia Berhad (TM). TMI was then demerged from TM and listed on Bursa Securities on April 28th, 2008. In March 2009, TMI changed its name to Axiata Group Berhad and launched a new identity.

Initially known as Mutiara Swisscom Bhd, a product of a merger between Mobikom and Digi, Digi.com Berhad launched its completely digital mobile phone services in 1995. Digi was the first company to launch pre-paid services in January 1998. In strategizing its growth, Digi acquired a little advantage in having Telenor as its parent company and also sister companies. As stated on its website, through a press release in 2015, Digi is now Malaysia's most extensive 4G LTE network, with the potential of connecting 1 in 2 Malaysians to its high- speed internet services with population coverage of 50%.

In March 2008, as the market became saturated, U Mobile, a part of a resource-rich international conglomerate, appeared to challenge the three companies. U Mobile is a threat to the big three, comprising of Maxis, Celcom, and Digi. The firm, however, is inferior regarding infrastructure or sales structure development to the incumbents. To compensate for what the company lacks, U Mobile and Maxis went into a multi-billion-ringgit agreement in October 2011 to share Maxis' 3G radio access networks (RAN) with U Mobile. Initially, a 10-year contract agreed by both parties, but in 2017, the network agreement announced to terminate to focus on expanding its network.

According to the latest data released by TowerXchange on its website, an independent media platform for the tower industry, there are an estimated 22682 towers in Malaysia for mobile communications, representing almost 2000 mobile subscribers per tower. Among 4 of the CSP mentioned above, Celcom tops the chart with 4000 towers, owned by edotco Group Sdn. Bhd., a subsidiary of Axiata Group Berhad, followed by Maxis with 3800 towers, Digi with 3400 towers and U Mobile with 1000 towers.

Based on the Malaysian Communications and Multimedia Commission (MCMC)'s Network Performance Report 2019, it concluded that the performance of a CSP has a relationship with the tower count of the CSP. Maxis, Celcom, and Digi emerge as the three leading CSP in terms of performance; hence these CSPs were chosen for this research. The next section covers in-depth about reputation index.

2.2 Reputation Index

The net effective or emotional reaction represented by corporate reputation and is involved in the overall estimation where its constituents hold a company. The reputation index described as a means to measure corporate reputation. One of the most common indices is the Net Promoter Score (NPS). NPS is a customer credit score developed by Fred Reichheld, a partner at Bain & Company in 2003. It assesses an organization's treatment of the people and also how well it generates loyal relationships. By acquiring this score, companies can develop strategies to focus on endorsing their brands.

In recent years, many companies, namely CSP, are focusing more on customer loyalty to gain profitable growth. NPS is increasingly used to increase and improve reliability on different levels within the organization. This metric gotten by asking customers whether they will or will not recommend the company to a family member, friend, or colleague on an 11-point scale. The NPS of the company calculated by subtracting the proportion of respondents rating the company a 6 or less, labeled "Detractors" from the portion of respondents rating the company a 9 or 10, labeled "Promoters". The formula was introduced by Reichheld in 2003 [13].

An alternative index proposed to make up NPS's flaws, which is Net Brand Reputations (NBR), through sentiment analysis. The differences between NPS and NBR showed in Table 1.

Table 1: Comparison between NPS and NBR

NPS	NBR
Data collection is done by asking for recommendations from customers	Data collection is done by extracting social media comments
The score represents only the existing customer's view	The score represents the view of the entire population without segmentation
Quantitative measurement with the following parameters: • Promoter (9-10) • Passive (7-8) • Detractor (0-6)	Quantitative measurement with the following parameters: • Positive • Negative

The purpose of NBR is to simplify the process of gauging consumers' loyalty. The index helps in focusing on creating more positive remarks and decreasing the negative feedback. NBR scores do not reflect the scores obtained using NPS. Thus, NBR is chosen as the reputation index for this project as it suits the nature of this project better, and it addresses the issues faced by NPS. In the next section, sentiment analysis extensively discussed.

2.3 Sentiment Analysis

Sentiment analysis, or opinion mining, refers to the broad area of natural language processing, text mining, computational linguistics, which involves the computational study of sentiments, opinions, and emotions based on emotion expressed in a text [14]. View or attitude based on feeling instead of the reason is often colloquially referred to as a sentiment. As defined by [15], sentiment analysis as a natural language processing and information extraction task that aims to obtain the writer's feelings expressed in positive or negative comments, questions, and requests. There is an increasing demand for sentiment analysis due to the need to analyze and structure the hidden information [16]. The biggest challenges of sentiment analysis are implicit sentiment and sarcasm.

Part-of-speech like adjectives, adverbs, and some groups of verbs and nouns are good indicators of subjectivity and sentiment. Syntactic dependency patterns by parsing or generates the dependency using part-of-speech, as claimed by [17]. It has determined that adjectives are reasonable indications of sentiment in text, and in the last 10 years, they have regularly exploited in sentiment analysis. Part-of-speech information is most commonly utilized in all-natural language processing tasks, mainly because they provide a crude form of word sense disambiguation. [18] also stated that appending part-of-speech tags to every word to some extent improves the Naïve Bayes (NB) accuracy.

The classification model takes after the name of the person who introduced the Bayes Theorem, Thomas Bayes. NB classifiers are simple linear classifiers, tending always to deliver. In theory, Bayes' theorem with strong (naïve) independence assumptions among the features applied to this classifier. In practice, the independence assumption frequently disregarded, but NB classifiers are still inclined to work fine under this unrealistic assumption. Especially for small sample sizes, NB classifiers can outclass the more powerful alternatives [19].

NB makes unrealistic independence assumptions, yet it tends to be surprisingly effective in practice since its classification decision may frequently be right even if its probability estimates are imprecise. It supported by [20], stated that NB is the most accurate and can regard as the baseline learning method, alongside SVM. Also, NB outperforms SVM when the feature space is small. Despite being simple, and also considering that its conditional independence assumption does not hold in real-world situations, NB still tends to work well.From the survey of different algorithms of sentiment analysis, it concluded that NB is the most suitable algorithm to be used for this particular project since it offers fast and good performance despite its simplicity. Moreover, it takes a robust approach to irrelevant attributes, improving its performance in handling classification tasks. Lastly, it is easily adaptable to changes as it works well with incremental updates, suiting the nature of this project.

2.4 Visualization Techniques

Data visualization defined as data representation in some systematic form, including attributes and variables for the unit of information. Data visualization helps business users integrate various data sources to create custom analytical views. Advanced analytics utilized to support the creation of interactive and animated graphics on desktops, laptops, or mobile devices such as tablets and smartphones [21]. In recent years, due to the high demand for vast, massive information to be represented, many visualization techniques have been developed [22].

There were few conventional data visualization techniques usually used to visualize the trend, such as pie chart, bar graph, and word cloud. A pie chart is also known as a circle graph that represents the information statistics and data in a manner, so it is easy to read. Commonly it is known as "pie-slice" form, and the different sizes of slice show how much of an element is in existence [23]. Pie chart visualization works well when comparing a segment of the pie chart to the rest of the portions of the pie chart, but it can be hard to compare different pie charts and a different section of varying pie charts among each other.

The bar chart is also called a bar graph. In some literature, the bar chart referred to a column chart. A bar chart used to visualize discrete data instead of continuous data. When the values to be represented are mostly different, it could prove to be suitable, but the suitability decreases as the value of differences decreases. The differences in the height of the bars will not be too distinct.

Word clouds summarize the content of websites or text documents in a simple yet fun way, contributing to its rise in fame in both websites and text analysis systems. In a typical word cloud, tags from a website, or words from a document are packed into a rectangular region in which font size indicates tag popularity, or word frequency, and font color shows other useful information [24]. A word cloud visualization method takes a list of words as the input, with their respective associated frequency value, and graphically illustrates the information Several visual representations created for word clouds over the years. At this point, the most popular way is positioning the words in an unordered layout, to optimize the use of space, and mapping the frequency values to the size of the font. Visual encoding tends to draw the attention of the user. Font size plays a significant role as it is easier to remember larger fonts. Furthermore, larger fonts are regularly assumed to refer to more significant words [25].

3. CONCEPTUAL MODEL DEFINITION AND REQUIREMENTS

There were many researchers described on the definition of the conceptual model (CM) from various perspectives, depending on the field explored. For this study, we found two aspects of CM that used to derived the ideas: (i) Simulation in Modeling CM (2008); and (ii) Integrated Framework for CM (2016).

3.1 Simulation in Modeling Conceptual Model

The Simulation Study CM by [26] is exploring details in the information technology viewpoint in designing and developing the application. The first model of the information system represented simply to be understood by all project team participants and developed more quickly to meet the requirements during the knowledge acquisition. The ideas are to ensure that the models developed faster, more flexible, require less data, run faster, and easy to interpret the results due to the understood structure of the model. The model designed for a specific purpose, and it is impossible to create an appropriate simplification without knowing the defined goals.

From the problem in the real world, the modeling starts with the key artefacts of CM, as in Figure 1, which consists of four components. It started with the system description, conceptual model, model design, and computer model. The system description refers to the problem domain; it explains the problem and the real-world elements connected to the problem. The CM belongs to the model domain, describes parts of the system description included in the model of simulation, and at what level of detail. The flow of information about the real world feeds into the narrative of the system represents by the arrows. The dashed arrow shows the computer model is in correspondence with the real world.

Figure 2 illustrates the framework of CM by Robinson, which involves five phases:

- Understanding the problem situation
- Determining the modeling and general project objectives
- Identifying the model outputs (responses)
- Identify the model inputs (experimental factors)
- Determining the model content (scope and level of detail)

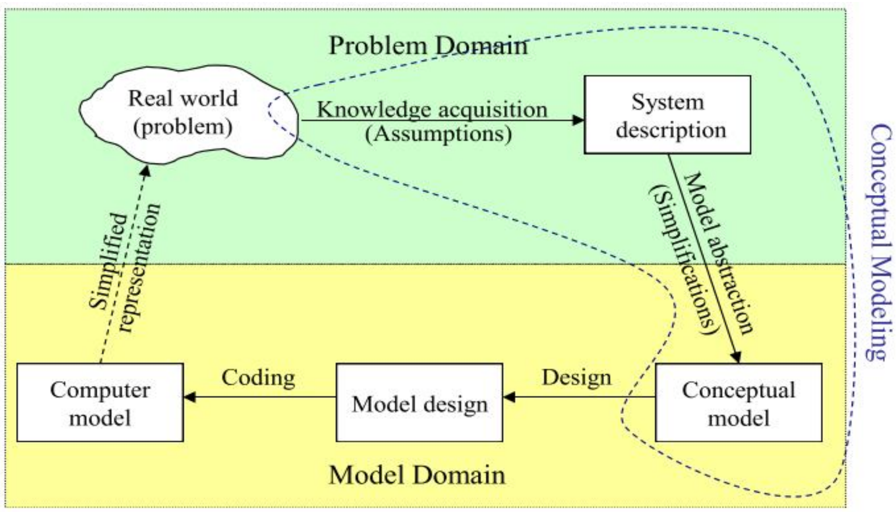

Figure 1: Artefacts of Conceptual Modeling [26]

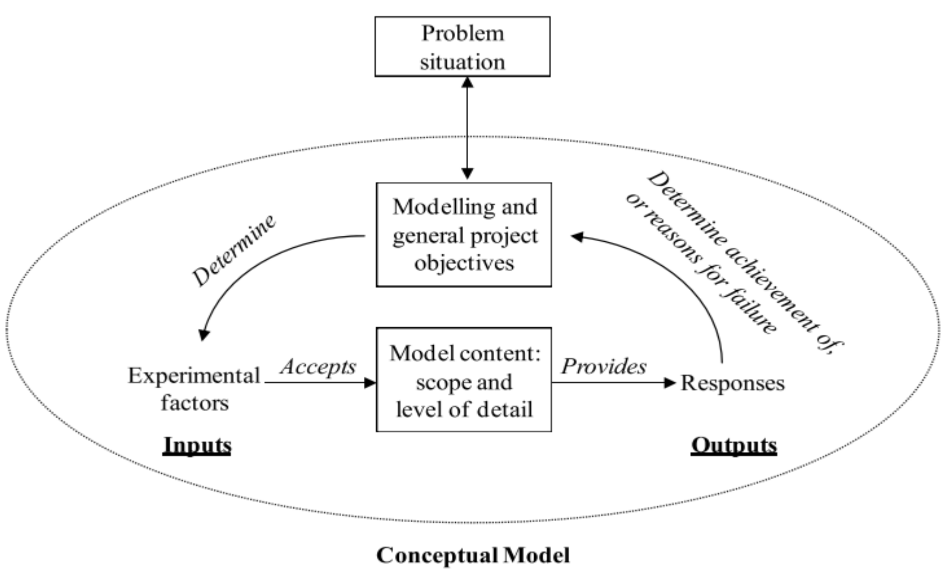

Figure 2: A Framework for Conceptual Modeling [26]

There is no specific ordering for the activities and more interaction expected between the activities involved in the simulation study, which is the data collection and analysis, coding, verification and validation, experimental, and implementation. Details of it represented through the description of the tables and diagrams, such as the flowchart and use case.

3.2 Integrated Framework for Conceptual Model

In 2016, [27] introduced a new integrated framework that merges the functional and non-functional requirements in developing an information system. The following algorithm of the proposed integrated system for computational modeling is an outcome of the literature review, study gaps identified, and work experience identified. The goal of this integrated process is to enhance the consistency of system specifications and the information system. It involved the functional and non-functional requirements, which consists of five steps, and using the method called as joint approval requirements.

- Guideline for the functional and non-functional requirements documentation – requirement gathered from the texts and documents, observations, interviews, and survey.
- Guide for quality of modeling instructions – using the modeling instruction.
- Guide for graphical representation of integrated conceptual model – using the quality of modeling instructions and requirements document.
- Instrument for designing an integrated conceptual model.
- Applying the approval requirement method – review and approve the requirements.

In the process of comparing both CM, we found that both contribute to the strengths and advantages in developing the CM for visualizing CSP reputation during the Covid-19 pandemic.

4. THE PROPOSED CONCEPTUAL MODEL

As CM specified and described on how the system organizes and operates [28], we identified the related components as below:

- Metaphors and analogies – the information is extracted from Twitter.
- Concepts – the items (with attributes: twitter account, name, status; with actions: log-in, log-out, comments negative or positive), subtypes of the item (periodical time: using pandemic Covid-19).
- Relationships – 1 user can have one or many twitter comments.
- Mapping – each item in the system corresponds to the user. The menu in the system has a link between the user interfaces (UI). Each of the CSP has its own menu.

Based on the reviewed research model earlier, since our objective is to have a proper and better visualization of the reputation in detail, we adapted the ideas from both models, and develop the requirements according to the study. The visualization must cater to the objectives such as to have a user-friendly application following the simulation idea, so the user can view the data available after considering the functional and non-functional requirement from the user. The model consists of eight elements, as in Figure 3.

4.1 Problem Situation

The CM starts with the problem situation. We have identified two main problems for this study:

1) Not enough sentiment analytics for non-English languages and social media in non-English languages gets more popular.
2) CSP used NPS (Net Promoter Score) to measure their customers' loyalty and satisfaction - only targeted existing subscribers.

4.2 Datasets

Datasets for the training set and testing set for this project extracted from huseinzol05's GitHub repository named Malaya-Dataset. The public can access this repository at https://github.com/huseinzol05/Malaya-Dataset. From the readme file, the repository claimed to gather and store Bahasa Malaysia corpus. The data are mostly collected using crawlers, and these data are semi-supervised by paid linguists. The data specifically used for this study extracted from two folders of the repository, which are Sentiment Twitter and Sentiment Multidomain.

4.3 Twitter Data

The identification of the metaphors and analogies extracted information from twitter, and each of it has its concepts. It is parallel with the scope of the study, specifically the items involved. Thus, we knew that twitter account consists of attributes such as username, log date, log time, link, location of the current place, and tweet details.

The language used is in English, Bahasa Malaysia, and can be both, which comprises of positive comments and negative comments. The data extracted using Twint, not the commonly used Twitter's API. Twint utilizes twitter's search operators to allow scraping from specific users and tweets relating to certain topics, hashtags, and trends. In this research, tweets that contain the keyword 'Celcom', 'Digi', and 'Maxis' dated from March 18th, 2020 to May 31st, 2020 scraped.

4.3 Data Pre-Processing

Data pre-processing or data cleaning is done to discard any unnecessary qualities in the data, which would make the trained model a poor generalizer. The data for real-world implementation pre-processed by removing the columns that are insignificant for this project—the final dataset comprised of three columns, which are date, username, and tweet. Tweet still carries the items identified as the scope. The cleaned data are then stored.

4.4 Naïve Bayes Classifier

The sentiment analyzer is built on top of the NB Classifier Model. In summary, the model learns the correct labels from the training set and performs a binary classification. The model assumes that the presence of a particular feature in a class is unrelated to the presence of any other function. The NB theorem calculates the probability of a specific event happening based on the probabilistic joint distributions of certain other events.

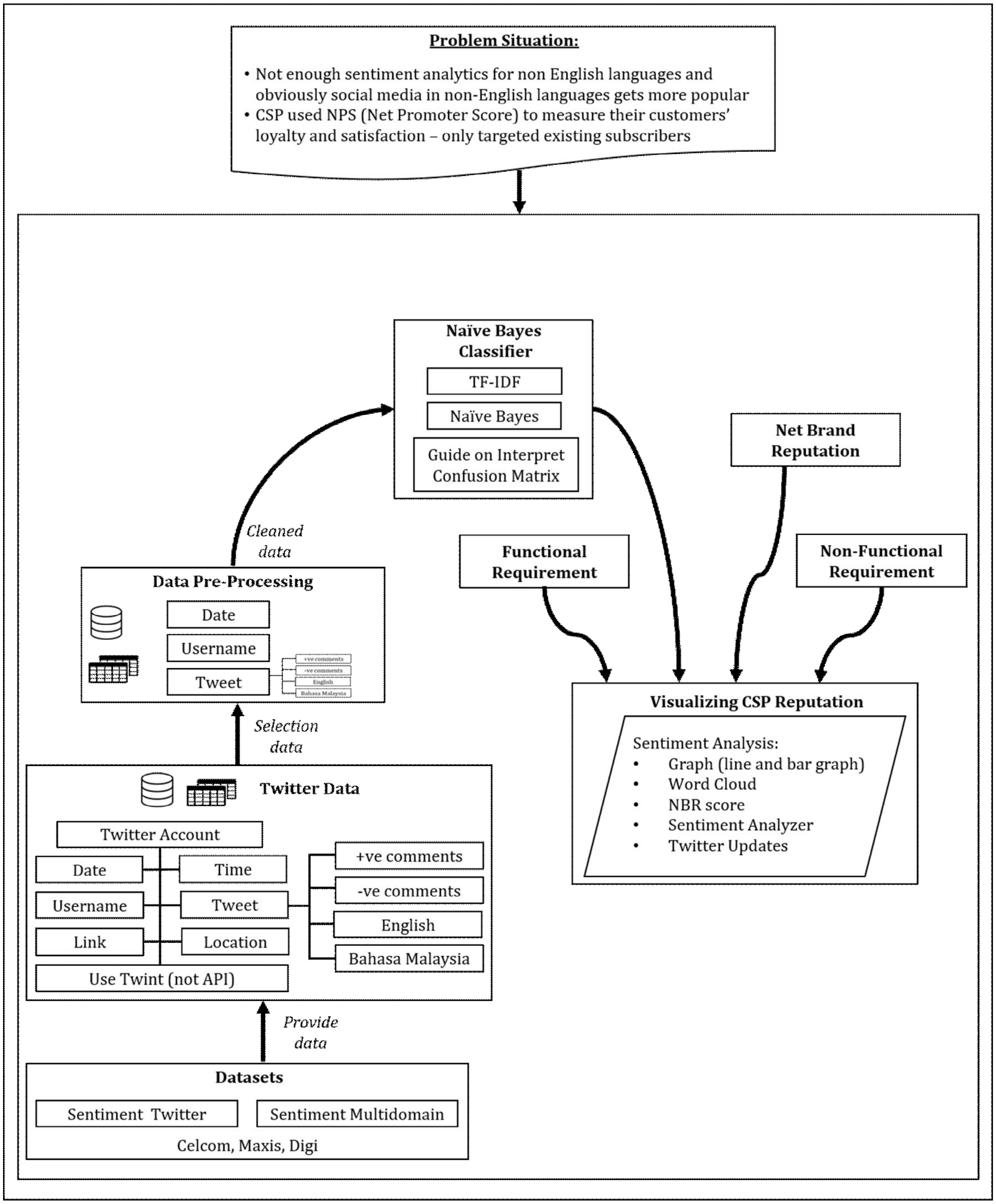

Figure 3: The Conceptual Model for Visualizing Reputation of CSP Through Twitter Sentiment Analysis

The first two steps are also commonly known as term frequency and inverse document frequency. These two are combined to form Term Frequency, Inverse Document Frequency, or TF-IDF, a weight widely used in information retrieval and text mining. This weight is a statistical measure used to evaluate the level of significance of a word to a particular document in a collection or corpus. The level of significance increases proportionally to the number of times a word appears in the document but is offset by the frequency of the word in the corpus.

Term Frequency (TF) is a measure of how frequently a term appears in a particular document. Since every document varies in length, a term would possibly occur many more times in longer documents than shorter ones. Thus, the term frequency is usually divided by the document length as a way of normalization.

Inverse Document Frequency (IDF), on the other hand, measures the level of significance of a term. While computing TF, all terms considered similarly significant. However, certain terms such as "is", "of", and "that" have the tendency to appear more frequently while adding little to no significance. Thus, the frequent terms need to weigh down, and the rare ones need to scale up at the same time.

The model is then stored and can retrieve in the future without having to retrain it. Model evaluation is then performed on the trained model to predict the unseen test data, which allows grading and retrieving the performance metrics. Two metrics are retrieved, which are the classification report and the confusion matrix.

4.5 Net Brand Reputation

In the real world of implementation and data visualization, Sentiment analysis based on the trained NB Classifier Model is then performed on the data to generate new data with the texts tagged with either a "positive" or a "negative" label, which is represented by "0" and "1". "0" represents "positive" and "1" represents "negative". These data are sorted according to the date and saved.

4.6 Functional Requirement

Functional requirements divided into two categories: functional user requirements and functional system requirements.

1) Functional user requirements are statements of high-level about what the system should be doing. It was written as statements of what services the system expected to provide and the constraints under which it must operate using a natural language and diagrams.
2) Functional system requirements describe clearly the application in detail, specify something that the application should do, describe a particular behavior of a function when it met certain conditions, such as displaying the word cloud, the CSP details information, and the NBR value.

To cater to both user and system requirements, we have to create a relationship between both using the use case diagram and flowchart. We will elaborate on the sequence of actions and the interactions involved to achieve the objectives. For example, the function of view the Celcom page. We have to ensure that the user is able to browse through the Celcom page where extensive details of the analysis conducted on Celcom's data from March 18th, 2020, to May 31st, 2020, displayed. For the flowchart, we displayed the overall system diagram with the specifically selected condition start from the landing page until the exit function.

4.7 Non-Functional Requirement

Non-functional requirements specify the performance of the system in certain functions, how the system should behave, and limits on the functionality. It is essential due to it will affect the user's experience when they are interacting with the system. There are four examples of non-functional requirements; usability, reliability, performance, and supportability.

1) Usability – Prioritize the crucial functions of the system based on usage patterns, frequently used functions should test for usability, and complex and critical functions should also test their usability.
2) Reliability – Users have to trust the system; no matter how long and how frequently used the system, the requirement of the data retained without any changes by the system for several years, and requirements for the easier way to monitor the system performance.
3) Performance – Few essential points such as the response times in any circumstances and any specific peak times of the system or stress periods.
4) Supportability – Cost-effective in maintaining the system, diverse documentation involved system, and test documentation.

4.8 Outcome of CM: Visualizing CSP Reputation

As the outcome from the CM, we able to develop an application that caters to all the information needed through the seven elements discussed. Details of the specification as below:

1) Graph – line graph used to illustrate the trend of sentiment in the period time of March 18th, 2020, to May 31st, 2020, weekly. It consists of "positive" and "negative"

tagged tweets and able to see the classification of the tweets. The bar graph displays the comparison of the total number of tweets between the CSP (Celcom, Maxis, and Digi) in percentage based on the same tagged tweet.

2) Word Cloud – it will be generated following the CSP data, respectively. Based on it, we able to see the biggest issue according to the most frequent term of word used.
3) NBR score – Comparison of the results for three CSPs is calculated based on the total number of tweets, the total number of positive tweets, and the total number of negative tweets to get the NBR for each CSP.
4) Sentiment Analyzer – Users can test the sentiment analyzer function. The system provides one text box displayed for the input, and the output is displayed next to it.
5) Twitter Updates – User able to displays the page of twitter updates. Tweets from the official accounts of the CSP streamed and displayed.

Figure 4 shows the proposed UI that consists of three CSP's and the summary analysis comparison.

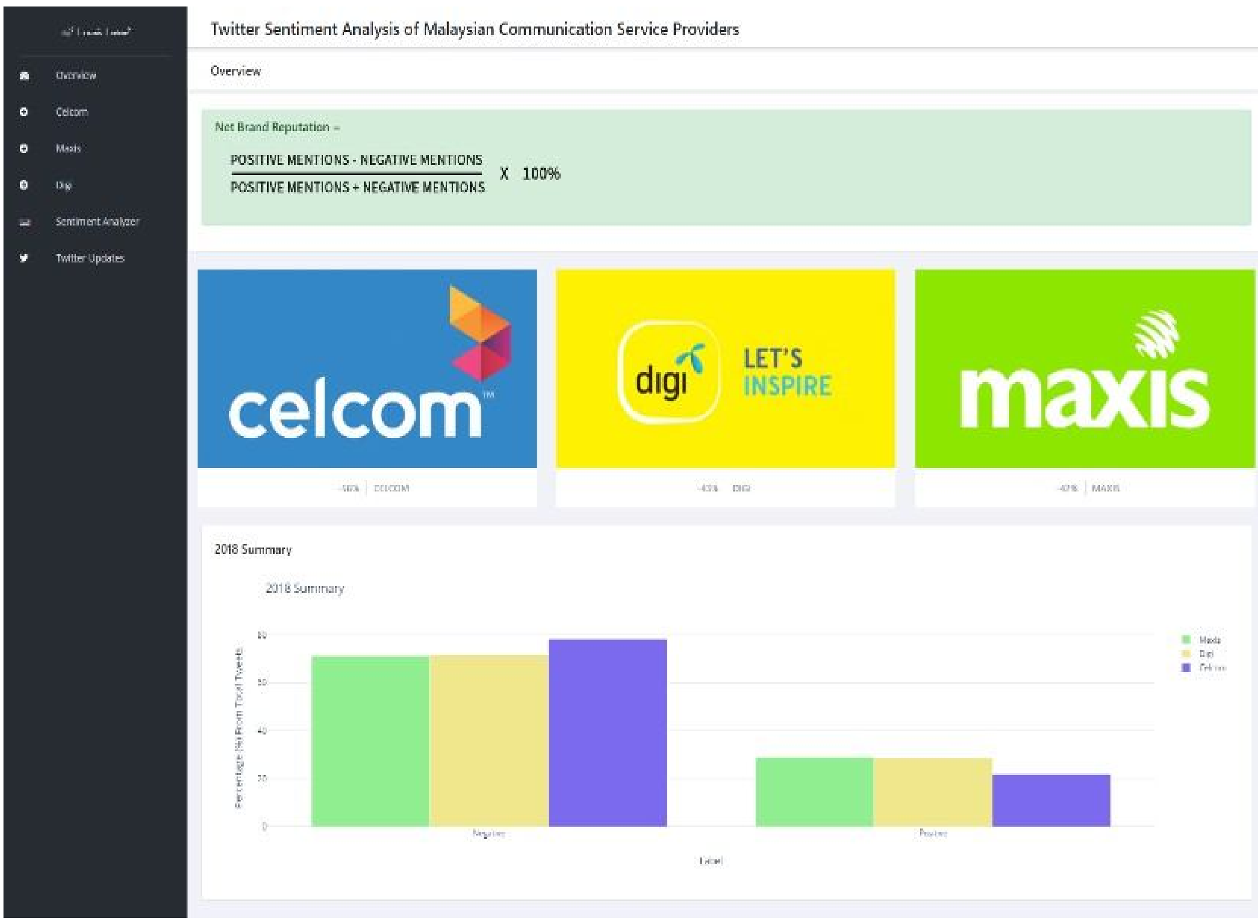

Figure 4: Proposed User Interface for Overview Page

5. CONCLUSION

This paper presents the conceptual design before the application designed. The main objective is to visualize the reputation of the top 3 CSPs in Malaysia, which is Celcom, Maxis and Digi, during the pandemic of Covid-19 using twitter sentiment analysis. It focuses on closing the two gaps mentioned in the problem statement that is not enough sentiment analytics for non-English languages, and most CSPs used NPS to measure customer loyalty. The implementation adapted the design process and activities. As a result, we found eight elements that contributed to the CM development starts with the problem, and focus on functional and non-functional requirements. It is at the boundary between different perspectives, and we bridge them. The proposed CM able to improve the services provided, appreciation for customers, and generates more profits. In the future, the application can be developed on the website platform, and anyone can use it as real-time information on the CSP's performance.

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