AN ANALYSIS OF PUBLIC PERCEPTION TOWARDS TECHNICAL AND VOCATIONAL EDUCATION AND TRAINING (TVET) ON THE FACEBOOK PLATFORM UTILISING LEXICON-BASED APPROACH

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ABSTRACT: The Malaysia government consistently emphasises the importance of Technical and Vocational Education and Training (TVET) as a crucial asset for the country, pushing all parties involved to prioritise it. Due to the rapid increase in social media usage, the public is becoming more likely to use social media platforms to interact and discuss various challenges in this field. An abundance of ideas can be accessed on the internet and should be employed to comprehend the viewpoint of important individuals involved and make necessary alignment to strategies and services. Unlike fields such as healthcare, business, and tourism, numerous sentiment studies have been conducted to examine the public perception with the goal of improving both services and products. However, there has been little investigation conducted on TVET. Therefore, this study is conducted to fill the gap by extracting TVET data from Facebook pages and public groups. The sentiment applied term frequency-inverse document frequency (TF-IDF) vectorization for extraction of valuable information evaluated by employing the accessible lexicons, namely Sentiwordnet, Valence Aware Dictionary sEntiment Reasoner (VADER), TextBlob, and AFINN. The evaluation results revealed that all lexicons exhibit a positive sentiment towards TVET. Moreover, by knowing the sentiment, it can facilitate policy makers and decision makers in formulating policies and strategies, as well as tackling existing difficulties and challenges for an enhanced TVET environment in the future.

KEY WORDS: *Sentiment, TVET, Lexicon, Accuracy, Recall, Precision, F1-score*

1. INTRODUCTION

Technical and Vocational Education and Training (TVET) is defined by UNESCO-UNEVOC as a set of educational programmes that are specifically related to the workplace. TVET encompasses both formal and informal learning approaches that equip youth with the know-how and abilities needed to become skilled workers and significantly contribute to economic growth (Wei Zhi & Anisah Atan, 2021; Yusoff et al., 2020). Additionally, TVET prepares young people for self-employment and job creation in the labour market (Mahuyu & Makochekanwa, 2020).

Currently, an enormous amount of social media data collected from multiple platforms in various formats can be simply and rapidly accessed (Kobayashi et al., 2018; Moe & Schweidel, 2017). Data obtained from social media can provide substantial and convincing insights. This information can facilitate the process of making well-informed decisions regarding future developments and policies (Baragash et al., 2022). Sentiment analysis or opinion mining is the process of extracting people's opinions, emotions, attitudes, and feelings about a topic or situation from a large amount of unstructured data (Mujahid et al., 2021). Sentiment analysis is more vital in the present digital age, as social media has emerged as a significant platform for user-generated information (Khan et al., 2024). Sentiment and opinion words often act a crucial part in the sentiment annotation of a document or sentence (Catelli et al., 2022). The primary aims of sentiment analysis is to understand people's viewpoints about certain topics, services and products which play an important role in decision making. Identifying the sentiment and opinion words can help to categorise the sentiment in an unsupervised manner (Dolianiti et al., 2019). Sentiment analysis helps us understand the thoughts, feelings, and views that people express online by figuring out the emotional tone behind a collection of words (Hermansyah & Sarno, 2020).

Sentiment analysis techniques can be categorised using machine learning, lexicon-based or hybrid techniques (Alharbi & Alhalabi, 2020). Machine learning technique performs selected algorithms such as Naïve Bayes, Support Vector Machine (SVM), and decision tree, to classify data into training and testing dataset. The lexicon-based technique uses pre-existing lexicon resources such as Sentiwordnet that contain the polarity of sentiment words to determine the polarity of a phrase (Rajeswari et al., 2020). The lexicon-based technique is often preferred over machine learning for sentiment classification due to its ability to provide flexibility in creating a customised sentiment vocabulary for emotion classification and does not rely on training data and consistently performs well across various domains (Rajeswari et al., 2020; Trivedi & Singh, 2021). However, lexicon that has attained a higher accuracy in one specific domain may not exhibit satisfactory performance in a different domain (Mohamad Sham & Mohamed, 2022).

Thus, this paper employs a lexicon-based technique to assess sentiment in TVET. The lexicons like SentiWordNet, VADER, TextBlob, and AFINN are employed and compared to determine the most reliable lexicons regarding accuracy, precision, recall, and F1-score value. The TVET dataset was subjected to preparation and pre-processing processes to lessen the presence of noise in the dataset. TF-IDF is performed for feature extraction prior to conducting sentiment analysis.

2. RELATED WORKS

Multiple approaches are employed for sentiment analysis, with the strategy chosen depends on the type of data and the platform being used (Mujahid et al., 2021). The lexicon-based approach is utilised in different industries, including business, education, healthcare, and tourism to figure out the perception and satisfaction levels of their services and products. Banerjee et al. (2021) examined the anticipations of social media users regarding information systems products that are currently at the conceptual phase and have not been released yet. An analysis was conducted on Twitter data pertaining to upcoming smartphones and smartwatches from Apple and Samsung. The polarity of the user's sentiment was determined using a lexicon-based technique, specifically utilising SentiWordNet. The dominant sentiment conveyed in tweets connected to Apple was neutral, whereas in tweets related to Samsung, it was positive. Furthermore, the analysis revealed that the percentage of tweets expressing negative sentiment was lower for Apple in comparison to Samsung.

Suhaimi et al. (2020) gathered Twitter data in English and Malay, specifically targeting concerns connected to Tun Hussien Onn Malaysia University (UTHM). Through the utilisation of a TextBlob lexicon, it was determined that all tweets could be categorised into three distinct sentiment categories which are positive, neutral, and negative. The analysis of English tweets revealed that 74% were positive and 26% were neutral. In contrast, an analysis of Malay tweets showed that 17% were positive, 82% were neutral, and 1% were negative. Examining positive and neutral sentiment revealed that individuals held a favorable view of the products and services, hence facilitating the international promotion and marketing of UTHM. Sukmana & Rusydiana (2023) conducted a study to examine the waqf education derived from Twitter platform. Their aim was to investigate sentiment and improve the waqf education practices in the future. They employed VADER lexicon to categorise the sentiment of each tweet. The results showed that in terms of sentiment polarity, the majority of tweets represented positive sentiment at 48.3%, followed by neutral sentiment at 27.0%, and negative sentiment at 24.8%.

In addition, Marcec & Likic (2022) performed sentiment analysis by employing the AFINN lexicon to monitor the sentiment concerning SARS-CoV-2 vaccine. A study was carried out on all English-language tweets mentioning the AstraZeneca/Oxford, Pfizer/BioNTech, and Moderna vaccines from December 2020 to March 2021. The results revealed that the sentiment towards Pfizer and Moderna vaccines remained consistently positive over four months. Nevertheless, the perception of the AstraZeneca/Oxford vaccine is gradually becoming more unfavorable, which could potentially increase reluctance toward this particular SARS-CoV-2 vaccination. Similar work was also carried out by Rizqiyah et al. (2024) to investigate the public perception of COVID-19 vaccinations in Indonesia using different lexicon. They utilised VADER to assess the opinions on the five most often given vaccines, including AstraZeneca, Moderna, Pfizer, Sinopharm, and Sinovac. Of the total, 39% expressed positivity, 18% expressed negativity, and 43% expressed neutrality. The general response of Indonesian population to each vaccine was predominantly positive and neutral. Sinopharm and Pfizer obtained the greatest sentiment scores, while AstraZeneca earned the lowest score.

The airline industry, specifically British Airlines, is also utilising lexicon-based approaches. Annamalai et al. (2024) conducted a study to identify the sentiment of individual customer evaluations and categorise them as positive, negative, or neutral by employing VADER lexicon. The study's findings indicated that customer reviews for British Airways have a predominantly positive sentiment polarity. By discerning positive and negative sentiments, the airline can comprehend its strengths and regions in need of enhancement. Acquiring essential information and recommendations can assist British Airways in improving customer experience and marketing tactics.

3. LEXICON-BASED APPROACH

Lexicon-based approaches can automatically assign labels without the need for manual labelling. However, the most difficult aspect of the lexicon-based approach in sentiment analysis is comprehending the domain or context. The dictionary-based approach is straightforwardly associating specific keywords with their corresponding sentiment. Any terms that are not included in the specified keywords or the opinions expressed in the given context will be disregarded (Shaik et al., 2023).

3.1. Sentiwordnet

SentiWordNet lexicon is extensively utilised in sentiment analysis due to its reliability and accuracy. SentiWordNet assigns a numerical value to each word in its database, indicating its positive and negative sentiment scores. As the score increases, the sentiment becomes more positive, and conversely, as the score decreases, the sentiment becomes more negative (Khan et al., 2024).

3.2. VADER

Valence Aware Dictionary sEntiment Reasoner (VADER) is a lexicon-based approach that works on gold-standard heuristics with sentiment lexicons written in the English language. The lexicons are assessed and verified by human. They employ qualitative methodologies to enhance the performance of the emotion analyzer (Reshi et al., 2022). VADER analyses text and combines the sentiment values for each word based on its position in the lexicon. Furthermore, it incorporates grammatical and syntactical principles to consider modifiers (like as "very" or "slightly"), negations, punctuation, and other contextual elements. A normalised compound sentiment score ranging from -1 (extremely unfavorable) to +1 (extremely favorable) is computed for each statement (Soni & Mathur, 2023).

3.3. TextBlob

TextBlob is a Python library that used to analyse textual data. It offers an API for tackling natural language processing (NLP) tasks including part-of-speech tagging, noun phrase extraction, sentiment analysis, and classification (Loria, 2020). Polarity identification is based on the distinction between subjectivity and objectivity, with subjectivity referring to personal opinions and objectivity referring to factual data. A sentiment score below 0 indicates a negative feeling, while a number above 0 indicates a positive sentiment. A score of 0 indicates a neutral sentiment (Reshi et al., 2022).

3.4. AFINN

AFINN lexicon derived from the Affective Norms for English Words lexicon (ANEW) in the English language, which was created by Nielsen (2017). Like VADER, it utilises a wide array of English words together with their corresponding sentiment scores. This approach employs a rule-based method, leveraging a meticulously created lexicon. The AFINN operates in a broader way, which is less intricate and requires fewer calculations (Reshi et al., 2022).

4. METHODOLOGY

The sentiment analysis of TVET involves a series of phases, as illustrated in Fig. 1. These steps include data collection, text preparation and pre-processing, feature extraction, sentiment analysis, and performance evaluation.

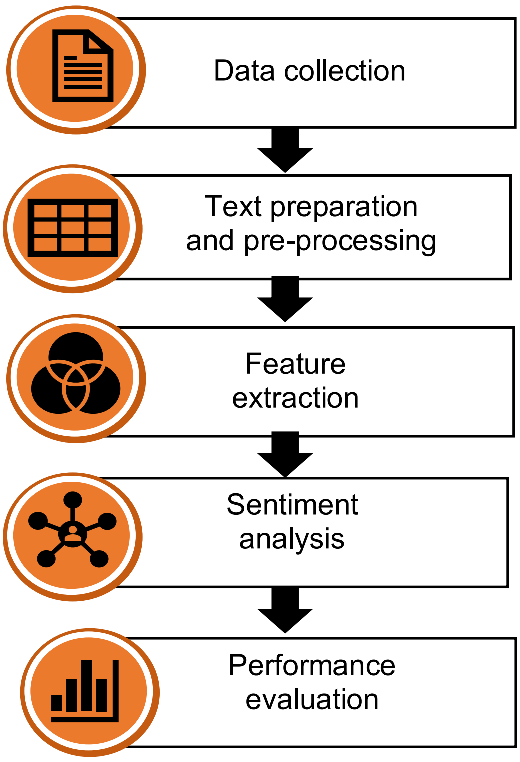

Fig. 1. Phase of works in sentiment analysis

4.1. Data Collection

The TVET dataset was acquired through the collection of data from Facebook pages and public groups. The collected data is specifically centred around posts and comments that relate to TVET. We gathered the data published from April 2021 to March 2023. Data is collected using two distinct applications, namely Facepager and Apify. Jünger & Keyling (2019) developed Facepager, a tool that utilises APIs and web scraping to retrieve publicly accessible data from platforms such as YouTube, Twitter, and other websites. The apify programme is utilised to gather data from a Facebook public group. The unprocessed data collected is retrieved as a .csv file. The file was converted into a .xlsx format by separating the content into columns, resulting in improved readability for posts and comments.

4.2. Data preparation and pre-processing

The data has been undergoing text preparation step. Text preparation involves the elimination of irrelevant text as well as the correction of misspelled words, abbreviations, and slang. The Malay data was subsequently translated into English. While data pre-processing involved several steps such as transforming text into lowercase, removing punctuation, and removing stop words. The number of posts selected for analysis after data preparation is 1,304.

4.3. Feature Extraction

Feature extraction is conducted to convert textual input into a numerical representation (Stanley et al., 2023). The term frequency-inverse document frequency (TF-IDF) is a commonly employed technique for extracting features (Reshi et al., 2022). TF-IDF uses two components to measure the relevance of words which are, TF indicates the importance of words while IDF displays the word distribution within the collection of documents (Edalati et al., 2022). In this study, TF-IDF is used because to its superior performance, particularly in enhancing accuracy measures.

4.4. Sentiment Analysis

Sentiment analysis uses Python programming code by importing lexicon libraries such as Sentiwordnet, VADER, TextBlob, and AFINN. Data polarities are categorised into three distinct classifications, which are positive, neutral, and negative. The compound sentiment score defines the polarity, which is determined using the relevant vocabulary. Afterwards, the evaluation of the lexicon's performance is calculated.

4.5. Criteria of Evaluation

To evaluate the classification of sentiment, four measurements were being evaluated which are accuracy, precision, recall, and F1-score. Accuracy is a metric that measures the likelihood with which a model precisely predicts the outcome (1). Precision indicates the frequency with which a model precisely predicts the target class (2). Recall is a quantify of the frequency with which a model precisely identifies positive instances (true positives) from all of the actual positive samples in the dataset (3). Lastly, the F1-score is a metric that measures the accuracy of a model on a given dataset (4).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1\text{- }score = \frac{2 \text{ x } precision \text{ x } recall}{precision + recall} \tag{4}$$

Whereas,

TP: the number of correctly classified positive values;

TN: the number of correctly classified negative values;

FP: the number of incorrectly classified positive values; and

FN: the number of incorrectly classified negative values.

5. RESULTS AND DISCUSSION

The results of this study are indicated that all the lexicons have a positive sentiment towards TVET data. TextBlob has the most higher positive polarity at 53.8%, followed by Sentiwordnet at 51.0%, AFINN at 47.7%, and VADER at 44.7%. For neutral polarity, AFINN shows higher percentage with 34.8%, VADER with 33.7%, TextBlob with 31.9%, and Sentiwordnet with 30.0%. On the other hand, negative polarity shows that VADER takes the lead with 21.6%, followed by Sentiwordnet with 19.0%, AFINN with 17.5%, and TextBlob with 14.3%. Fig. 2 presents the overall polarity percentage of TVET dataset.

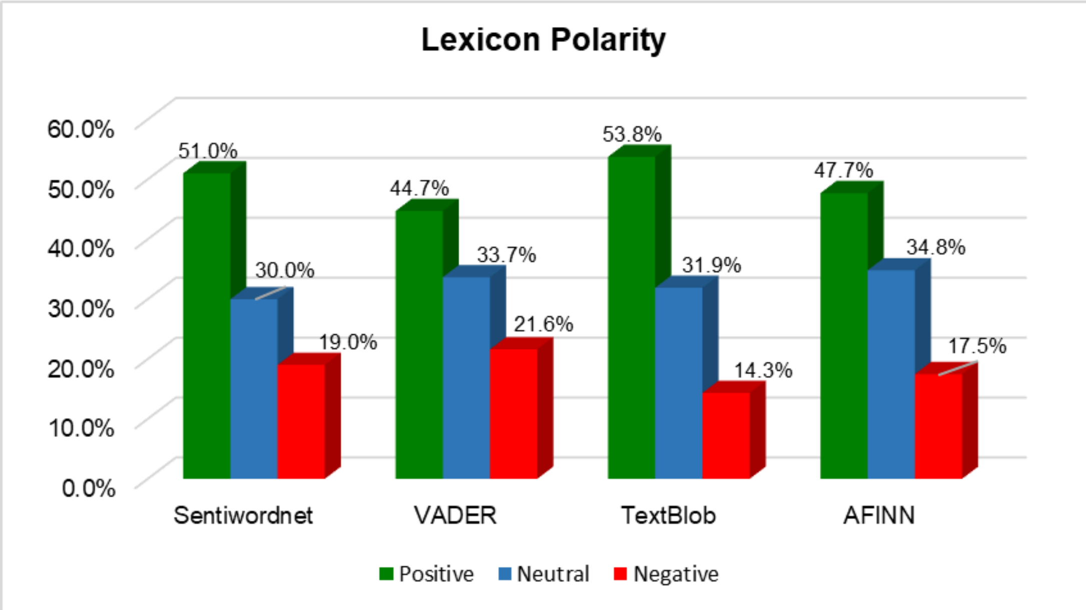

Fig. 2. Polarity of sentiment

Based on accuracy, this finding shows that the VADER lexicon outperformed other lexicons by achieving an overall accuracy rate of 69.9%, surpassing AFINN, which achieved 67.7%. Furthermore, TextBlob demonstrated a performance rate of accuracy with 61.9%, while Sentiwordnet attained a slightly lower rate of 54.9%. Fig. 3 shows the accuracy of TVET dataset performance.

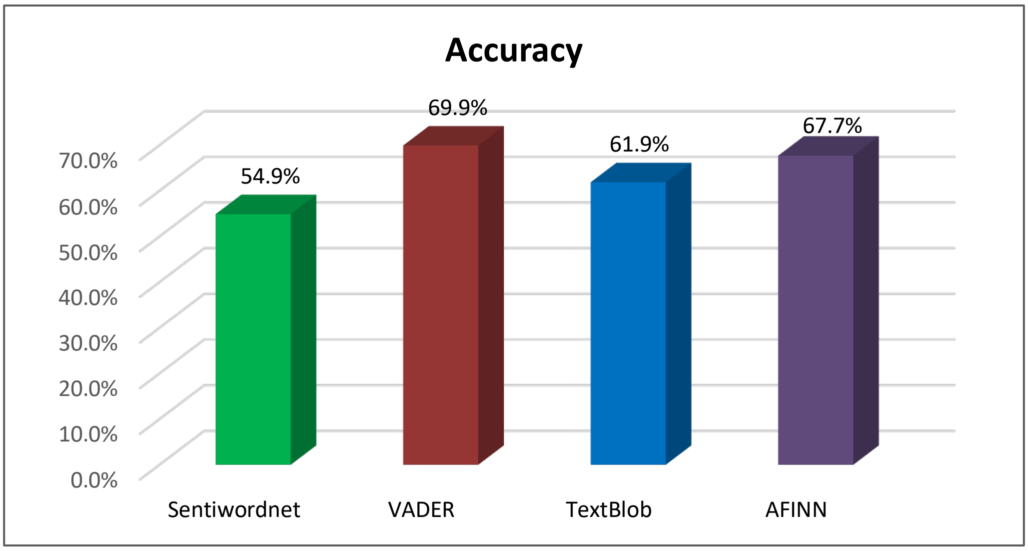

Fig. 3. Accuracy of lexicons

The VADER lexicon has shown excellent accuracy in correctly categorising positive and negative sentiment by prioritising the F1-score. VADER achieved the highest F1-scores of 0.76 and 0.63 for both positive and negative polarity classification. Table 1 shows the evaluation criteria for TVET dataset.

Table 1: Evaluation criteria in TVET dataset

Sentiment Lexicon	Accuracy	Positive			Neutral			Negative		
		P	R	F	P	R	F	P	R	F
Sentiwordnet	54.9%	0.63	0.69	0.66	0.53	0.33	0.40	0.39	0.53	0.45
VADER	69.9%	0.79	0.72	0.76	0.64	0.67	0.66	0.59	0.68	0.63
TextBlob	61.9%	0.67	0.69	0.68	0.55	0.64	0.59	0.60	0.40	0.48
AFINN	67.7%	0.78	0.72	0.75	0.60	0.71	0.65	0.58	0.53	0.56

P: Precision, R: Recall, F: F1-score

6. CONCLUSION

This study utilised a lexicon-based approach to determine the public's perception on Facebook regarding TVET concerns. Four distinct dictionaries, Sentiwordnet, VADER, TextBlob, and AFINN, are employed to determine the polarity and accuracy.

Based on the results of the study, all lexicons indicate a favourable opinion towards TVET. TextBlob has the highest positive classification, while VADER exhibits the highest percentage on negative classification sentiment. Additionally, optimal outcomes using these lexicons are also measured by calculating the accuracy. The outcome demonstrates that VADER lexicon shows superior performance, with a higher accuracy rate of 69.9% compared to other lexicons. Furthermore, VADER performs better in classifying positive and negative polarity, achieving the highest F1-scores of 0.76 and 0.63, respectively.

Therefore, the polarity gain can assist stakeholders involved in policy and strategy development in TVET in making more informed decisions to realign and enhance the TVET ecosystem. Further improvement can be done by implementing topic modeling for each polarity to identify specific themes and make targeted improvements accordingly.

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