TOPSIS in Decision-Making Framework Based on Twitter Sentiment Analysis

1st Erna Daniati
Information System
Universitas Nusantara PGRI Kediri
Kediri, Indonesia
ernadaniati@unpkediri.ac.id

2nd Hastari Utama
Informatic Engineering
Universitas Amikom Yogyakarta
Yogyakarta, Indonesia
utama@amikom.ac.id

***Abstract*—Twitter is one of social media that categorized in microblogging. Tweets on Twitter which are short sentences containing an opinion or sentiment. This is very beneficial for the organization or company to conduct analysis. The objective for this analysis is market prediction, general elections, measuring reactions to events or news, and measuring subjectivity. This affects the decision making for the company. Therefore, the role of sentiment analysis is very necessary to get the classification of sentiment in the form of positive, negative, and neutral sentiments. This type of sentiment polarity is used as a criteria for preference modeling so that alternative decisions can be calculated for the final value. This study attempts to propose a decision-making framework based on sentiment analysis. In addition, this research is also an improvement from the previous decision-making framework where decision-making is based on sentiment analysis. Improvements were made to the modeling of the criteria which initially used the SAW method to be changed to the TOPSIS method. Furthermore, the final value of the decision alternatives using TOPSIS is compared with using SAW. The comparison parameters used are in the form of final scores and ranking results. The final score of the SAW method is greater than the TOPSIS end score. In addition, there are differences in the ranking results between the TOPSIS and SAW methods.**

Keywords—TOPSIS, SAW, DSS, Sentiment Analysis, Framewok

I. INTRODUCTION

Twitter is one of many social media that has millions of users where they share their data with each other every day [1]. In fact, in this year social media has drastically communicated one person to another and is the key to the success of an organization [2]. As of July 2018, Twitter has millions of users and they can tweet 500 million per day. This indicates that Twitter as a social media has developed rapidly. In addition, Twitter is also used to find out information or trends that occur within a certain period of time.

Tweet in Twitter is a short sentence that can contain the opinions or sentiments of its own users. This is very potential for an organization or company to analyze it [3]. The results of this analysis are useful for predicting things that will happen or become a trend in the future. In addition, the analysis result can be a description of the structure in the entity relationship between tweet users. The activity of getting the results of this analysis requires sentiment analysis which contains a series of stages and is part of the Natural Langage Processing. Things that become objects of the results of this analysis are stock market predictions, general elections, measuring reactions to events or news, and measuring subjectivity. These results will be a guide for the company to make decisions that affect the company's policies.

Decision making for a company is a significant thing. Therefore, it needs to develop a management information system that can be callled decision support system (DSS). It effectively supports companies in managing promotions, products, and marketing [4]. This also cannot be separated from the role of social media that accompanies these activities. This DSS monitors various types of social media by collecting comments on products, promotions and services. This contributes to managers making decisions that are not based on intuition but based on modeling criteria and data support. These criteria are generated from the sentiment analysis process. Therefore, the resulting decisions are more effective and in accordance with the goals of the company and there are many decision choices for managers because several alternative decisions are available.

The role of sentiment analysis here is to produce classification results with the cumulative number of tweet types taken by the Sentiment Analysis Engine (SAE). SAE will generate sentiment classification results in the form of positive, negative, and neutral tweets and display these types along with their number. These types are used as the basis of criteria for preference modeling in the design phase of the decision-making phase. Modeling these criteria can use various Multi Criteria Decision Making (MCDM) methods such as Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Simple additive weighting (SAW), or . So, the core of this analysis rests on SAE and MCDM methods that seek to obtain alternative decisions with the aim of helping decision makers in making their decisions.

One type of MCDM method that will be used in this study is TOPSIS. This method is an effective method compared to other heuristic methods because this method has characteristics, namely few parameters, high consistency, and low computation [5]. TOPSIS tries to convert the response value to another form of value, namely the single response performance value. This method was built by Hwang and Yoon in 1981. The principle of the TOPSIS method is to find the shortest distance to the positive ideal solution value. On the other hand, it also looks for the furthest distance with a negative ideal solution value. This distance calculation uses the Euclidean distance. The positive ideal solution itself is a hypothetical solution where all attributes are related to the maximum attribute values in the data set. This data set consists of satisfactory solutions. Otherwise, The negative ideal solution itself is a hypothetical solution where all attributes are related to the minimum attribute values in the data set. So, the final value of the alternative decision generated by TOPSIS is a solution that is not only close to the best hypothesis value. However, this final value is also furthest from the worst hypothesis value.

This research is an improvement from the previous decision-making framework where decision-making is based on sentiment analysis. Improvements were made to the modeling of the criteria which initially used the SAW method to be changed to the TOPSIS method. This is done to determine the final score of the SAW method with TOPSIS. In addition, the consistency of alternative decision rankings is also compared so that it is known the difference in the results of ranking decisions with the SAW method against TOPSIS.

II. Sentiment Analysis

One method to analyze social media is sentiment analysis. Sentiment itself can contain variables that have positive, negative, and neutral values and even more specific values such as happy and angry [6]. Each variable can contain a long range of values according to the form of sentiment that exists in the world. This means that the values of positive and negative sentiments can be described again. Sentiment analysis also contains subjectivity, which means a comparison or ratio of positive to negative or neutral sentiment and vice versa. In addition, there is also a polarity which means a positive to negative ratio.

Sentiment analysis is the process of identifying the type of opinion or sentiment contained in a sentence, tweet, or corpus [7]. Sentiment analysis is carried out on texts from social media and is used to measure and analyze the level of customer satisfaction with products from a company. This makes a company interested in using the results of this analysis in determining policies so that it affects the course of business and supports the goals of the organization. .

III. Decision Making Phases

In an organization, decision making is very important. This decision-making is carried out by the management which affects the course of business processes in the organization. Decision making is a collection of several processes consisting of several phases. The purpose of this series of processes is to determine recommendations from alternative decisions that have been given a weighted value so that they contribute to decision makers in determining their decisions [8].

The existence of the decision-making phase gave rise to a Decision Support System. This system can interact with decision makers to contribute for solving in semi-structured and even unstructured problems based on computer system. This system was developed to assist decision makers in determining their decisions as potential solutions in dealing with problems related to organizational goals [9]. The decision making of the decision makers is based on the selection of alternatives that have been given a weighted value even though it is still subjective. This system has a contribution in structuring and solving problems faced and displaying transparency in decision making. In addition, DSS also provides users with a better understanding of problem conditions and promotes learning. So, DSS does not only provide value weights and preference modeling. Therefore, DSS has unique challenges related to decision making that are not experienced in traditional systems models or designs.

The decision-making process has been developed by Simon which consists of four phases, namely Intelligence, Design, Choice, and Implementation [8]. This decision-making phase is shown in Figure 1.

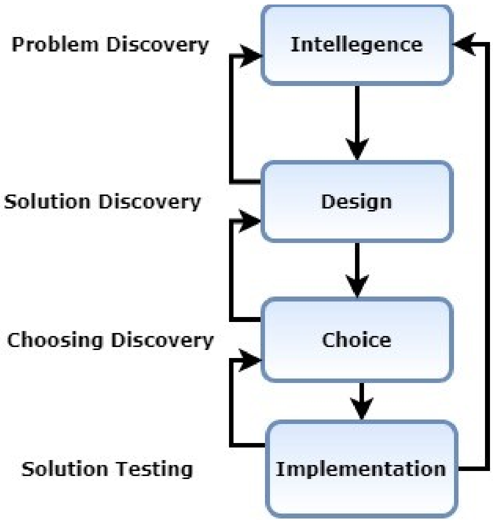

Fig. 1. Decision Making Phase

The first phase in Figure 1 is the intelligence phase. This phase contains the process to identify the goals and objectives of an organization against the problems it deals. In organizations, decision makers are generally staff in the management division. It is necessary to identify the problem and its characteristics so that the problem domain needs to be known basicly.

In the design phase, attempt to define and build a model for the representation of the system. This will determine the relationship of several variables that have been defined previously.In addition, this phase also includes modeling of some alternative decisions. These are going to be selected by decision makers. The design or model built can use some methods in MCDM such as Vikor, SAW, TOPSIS, AHP, etc. This model attempt to find a solutions that will conduct calculation for final score in alternative decisions. In this phase, the main role of DSS is shown in preference modeling.

The third phase is the choice or selection phase. Alternative decisions generated from the DSS are ordered based on the results of the calculation. This alternative decisions sequence is a recommendation to decision makers to select it where the selection is the result of decision making. The alternative decisions sequence is built by the final value of the decision modeling calculation. The effect of this recommendation is that decision makers make their decisions based on modeling or calculations from previous data and not based on intuition.

The last phase is implementation. Implementation phase contains the implementation of alternative decisions which have been selected by decision makers. The chosen alternative is implemented and its impact is evaluated. The results of these evaluation are feedback in the DSS and attempt to improve the next of the DSS . The feedback flow goes to the previous phase or directly to the beginning phase

IV. Multi-Criteria Decision Making

In the 1960s, Multi Criteria Decision Making (MCDM) was first built to help in decision making when dealing with problems of adapting different ideas and processing large amounts of complex information [10]. This prompted research into combining MCDM with geographic information systems. Multi-criteria decision making consists of several stages, namely i) defining goals, ii) selecting criteria to calculate goals, iii) determining alternative decisions, (iv) giving weights to criteria, and (v) applying calculations correctly for alternatives sequences. MCDM can overcome the integration of modern planning objectives where it is not related to separate identification and ranking of planning solutions.

This spatial MCDM method can increase the analytical and transparency problems of soil using decisions [10]. The practical application of the spatial MCDM method has become more expand in soil conformity studies. Recent studies demonstrating the implementation of MCDM method in identifying the coverage to which future soil use area are rare at a local scale. The most of previous MCDM implementation have actually related on using MCDM to rank the priority of initialized management selections or planning flow. However, spatial MCDM, can be used not only to rank selection priorities and perform scenario analysis, but also to provide insight into alternative spatial levels. This ability can contribute local soil use planners identify soil use area for future agriculture and urban development. This can be particularly useful in situations where the planning instrument does not provide prescriptive guidance for local planning decisions.

The MCDM methods consists of AHP, Fuzzy Set Theory, SAW, TOPSIS, and Random Set Theory provide more reliable algorithms for calculating uncertain or inaccurate data [10]. Fuzzy set theory method is recommended as technique for solving with incorrect and uncertain problems. Several the empirical research have applied fuzzy methods without comparative analysis to study whether using more reliable methods such as fuzzy AHP will make actually difference compared to conventional AHP. Otherwise, the few researchs that have conducted comparative analyzes in soil conformity implementation have focused on arithmetical aspects such as differences in criteria weights, selection ratings, or the effect of incorporating uncertainty in the models. This requirement to comparative analysis brings greater imperatives in the context of applying spatial MCDM technique to aquaculture world priority planning decisions, where simplicity and transparencyof decision-making models are the main elements during stakeholder consultations.

V. Technique for Order Preference by Similarity to Ideal Solution

Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) is one type of MCDM method. This method was built by Hwang and Yoon in 1981. The TOPSIS method attempts to calculate alternative values by calculating the positive ideal value which is far from the negative ideal value [10]. The positive ideal value is obtained from maximizing the value of the criteria benefit and minimizing the value of the criteria cost. Conversely, a negative criteria value maximizes the criteria cost value but minimizes the criteria benefit value or score. It can be said that the positive ideal solution is all the best score of the criteria, while the negative ideal solution is the bad score of the criteria.

The TOPSIS technique has several steps in calculating the final score of several decision alternatives. These steps are depicted in Figure 2 [10]. The description of these steps is as follows:

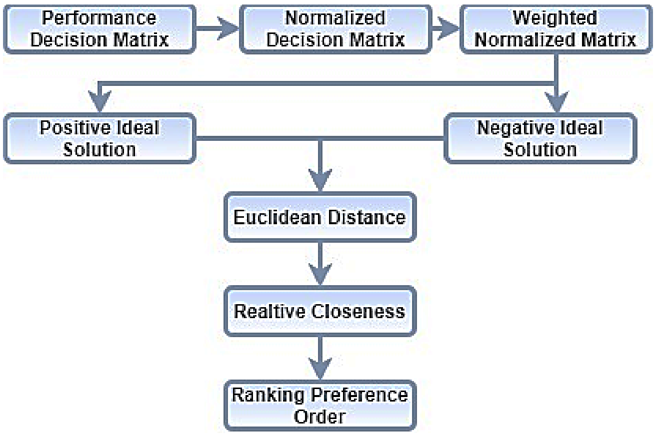

Fig. 2. Phases of TOPSIS Calculation

Step 1. Building a Performance Decision Matrix
The matrix structure built is shown in equation (1)

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \quad (1)$$

Step 2. Normalized Decision Matrix
The next step is normalizing the r_{ij} value by calculating the following using the normalized decision matrix in equation (3).

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{n} a_{ij}^2}}, i = 1, \ldots, m;\ \text{dan}\ j = 1, \ldots, n \quad (2)$$

$$r_{ij} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \quad (3)$$

where for r_{ij} shows the normalization value of the *j-th* criteria for the *i-th* alternative decision of A_i.

Step 3. Calculating weight of Normalized Decision Matrix

$$V_{ij} = R_{ij} \times W_{n \times n} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} \quad (4)$$

where w_j is the weight of the *j-th* criteria and $\sum_{j=1}^{n} W_j = 1$

Step 4. Decide the positive ideal solution (A_i^+) and negative ideal solution (A_i^-)

This is shown in equation (5) and (6).

$$A_i^+ = \{(max\ v_{ij} | j \in J), (min\ v_{ij} | j \in J'), (i = 1,2, \ldots, m)\} = \{v_1^+, v_2^+, \ldots, v_n^+\}\ or\ \{v_j^+\} \quad (5)$$

$$A_i^- = \{(min\ v_{ij} | j \in J), (max\ v_{ij} | j \in J'), (i = 1,2, \ldots, n)\} = \{v_1^-, v_2^-, \ldots, v_n^-\}\ or\ \{v_j^-\} \quad (6)$$

where A_i^+ denotes a positive ideal solution, and A_i^- denotes a negative ideal solution. J is the set of criteria with positive effects while J' is the set of criteria for negative effects.

Step 5. Calculate Euclidean Distance
Calculate the distance from each alternative decisions to the positive ideal solution and the negative ideal solution using m-

dimensional Euclidean distance. This is indicated by equations (7) and (8).

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \;, i = 1, \ldots, m \quad (7)$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \;, i = 1, \ldots, m \quad (8)$$

where for D_i^+ is a range between the *i-th* alternative decision for the positive ideal solution, and D_i^- indicates the range between the i-th alternative decision and the negative ideal solution.

Step 6. Calculates the relative proximity to the ideal solution. This is shown in equation (9).

$$CC_i^+ = \left[\frac{D_i^-}{D_i^+ + D_i^-}\right]; 0 \le CC_i^+ \le 1; i = 1,2,\ldots,m \quad (9)$$

Step 7. Conduct Ranking Preferences Order

After calculating the alternative proximity and the value of C_i, the next step is to rank the alternatives and sort the values of C_i

VI. Methodology

This research was conducted with an experimental approach or can be called experimental research. This involves a simulation situation where the research activity can manipulate one or more independent variables and measure the outcome variable [11]. A carefully designed and implemented experiment will be one of science's most powerful methods for establishing causal relationships. In this study, the criteria that become the input of preference modeling are the variables that will be manipulated by the data. This raises the observation of the results of the calculation of the final preference value.

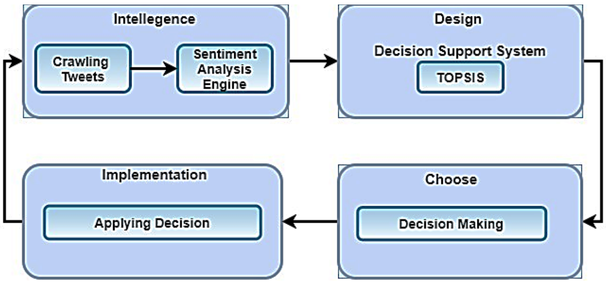

Fig. 3. Decision Making Framework into Sentiment Analysis

In Figure 3 is a description of the process contained by the decision-making phase which has been described in Figure 1. In the Intelligence Phase contains the Crawling Tweet process and there is a Sentiment Analysis Engine. Tweet crawling attempts to collect tweets that are loaded on Twitter based on predefined search categories. Furthermore, Sentiment Analysis Engine is a computer program that functions to classify a collection of tweets obtained based on positive, negative, and neutral labels. The polarity label is used as a criteria in the design phase. So the profit criteria are represented as positive and neutral labels but the weights are different. Meanwhile, the cost criteria are represented as negative labels. The number of tweets based on the label is the input for the value of each criteria.

In the design phase in Figure 3 there is a Decision Support System. This DSS uses the TOPSIS method to model its preferences or calculate the final value of alternative decisions. The criteria to be calculated are positive, negative, and neutral labels. The decision maker determines the weight value of each of these labels. Then, the criteria value is taken from the number of tweets from each of these criteria.

Figure 3 is the architecture of a decision-making framework based on sentiment analysis. This framework is a revision of the previous structure [3]. The difference between this framework and the previous one lies in the design phase where the preference or criteria modeling uses the TOPSIS method. In addition, there is a path that is continued from the Implementation block to the initial block, namely intelligence. This flow is feedback when the implementation of decisions is carried out at the implementation stage. If the decision applied is not appropriate or there are obstacles that are contrary to the decision-making phase, it is necessary to provide feedback as input so that there is a revision of the existing processes in the intelligence and design phase.

The structure of the Sentiment Analysis Engine (SAE) has also changed. The SAE architecture is shown in Figure 4. What distinguishes it from previous studies is the feature extraction stage. The features are obtained using the Word2Vec method. This method is one type of document representation using Word Embedding. The Word2Vec method is an improvement over the TF-IDF method. This method is able to insert semantic equations between words using Euclidean distance calculation [12]. Semantics between words are involved in document representation and not the frequency of occurrence of words and the frequency of documents containing only words. So, the order of words in the tweet is also calculated.

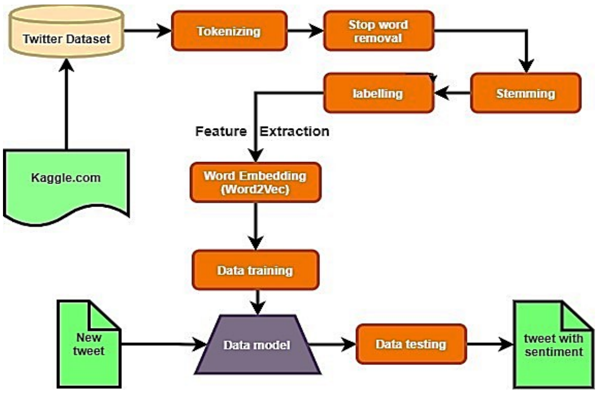

Fig. 4. Architecture of Sentiment Analysis Engine

VII. Result And Discusion

The decision-making framework proposed in Figure 3 will be experimented with with data taken from the gsmarena.com site. This data is a smartphone specification with 4 criteria shown in Table I. A decision maker in this case the buyer is faced with 3 choices of smartphones to buy. This, initially confused the buyer to determine his decision in buying the smartphone.

TABLE I. Smarphone List

Code	Name	Storage/ RAM (GB)	Camera (MP)	Price ($)	Battery (mAh)
A1	Realme Narzo 10A	32/3	12	199	5.000
A2	Xiaomi Redmi 9A	32/3	13	145	5.000

A3	Samsung Galaxy A20	32/3	13	125	4.000

The prospective buyer has the desire to determine one of the 3 kinds of smartphones he will buy. So, the three smartphones are an alternative decisions that the prospective buyer will select it. The initial step according to the suggested framework in Figure 3 is collecting tweets with keywords according to the smartphone name, namely Realme Narzo 10 A, Xiaomi Redmi 9A, and Samsung Galaxy A20. The search results produce the amount of tweets for each kind of smartphone, which is 20 because in SAE has been set for each keyword to produce a minimum in 20 tweets. The cumulative number of these tweets is performed in Table II. The number of positive, negative, and neutral tweets is used as a criteria value to be calculated using the TOPSIS technique. Furthermore, in Table II, a matrix consisting of criteria C1, C2, and C3 is compiled along with alternative decisions A1, A2, and A3 which are shown in Table III.

Each alternative decision needs to be given a weight for each of its criteria. This weighting is given by decision makers who have a level of interest in each weight. In Table IV the weights given to each criteria are given the same value, namely C1 = 5, C2 = 2, and C3 = 3. This refers to previous research regarding weighting with SAW [3].

TABLE II. CUMMULATIVE OF POLARITY TWEETS

Code	Name	Positive (C1)	Negative (C2)	Neutral (C3)	Total
A1	Realme Narzo 10A	10	4	6	20
A2	Xiaomi Redmi 9A	12	5	3	20
A3	Samsung Galaxy A20	11	4	5	20

TABLE III. PERFORMANCE DECISION MATRIX

Code/Criteria	C1	C2	C3
A1	10	4	6
A2	12	5	3
A3	11	4	5

TABLE IV. DECISION WEIGHT MATRIX

Code/Criteria	C1	C2	C3
A1	5	2	3
A2	5	2	3
A3	5	2	3

Furthermore, the Performance Decision Matrix in Table III is normalized using equation (2) which has been defined previously. The normalization results are shown in Table V. The normalization results are then multiplied using equation (3). Multiplication is carried out for each matrix element in Table IV against Table V which produces a Weighted Normalized Decision Matrix which is shown in Table VI.

TABLE V. NORMALIZED DECISION MATRIX

Code/ Criteria	C1	C2	C3
A1	0.52342392	0.52981294	0.71713717
A2	0.62810871	0.66226618	0.35856858
A3	0.57576631	0.52981294	0.5976143

TABLE VI. WEIGTHED NORMALIZED DECISION MATRIX

Code/ Criteria	C1	C2	C3
A1	5.23423923	2.119251771	4.302823
A2	7.53730449	3.311330893	1.0757057
A3	6.33342946	2.119251771	2.9880715

The next step is to calculate the value of the positive ideal solution represented by A_i^+ and the value of the negative ideal solution with the notation A_i^-. This calculation uses equations (5) and (6). The results of this calculation are shown in Table VII where the value of the positive ideal solution (A_i^+) is included in the criteria *C1*, *C2*, and *C3*. This is also the same as the value of the negative ideal solution (A_i^-) which is also included in each criteria.

The positive and negative ideal solution values that have been obtained are then used to calculate the distance between the weighted normalized decision values and the ideal solution values. This distance calculation uses Euclidean where equations (7) and (8) are used. The results of the calculation of the Euclidean distance from each alternative decision are shown in Table VIII. So, each alternative decision has a distance to the positive and negative ideal values. Each distance to the positive and negative ideal values is then calculated to get the final value. This final value calculation uses equation (9). The results obtained from the final score using the TOPSIS method are shown in Table IX.

TABLE VII. POSITIVE IDEAL A_I^+ AND NEGATIVE IDEAL A_I^-

Solution/Criteria	C1	C2	C3
Ai+ (max)	3.14054354	1.324532357	2.1514115
Ai- (min)	2.61711961	1.059625886	1.0757057

TABLE VIII. DISTANCE FOR EACH WEIGHTED NORMALIZED DECISION MATRIX

Code/ Criteria	D_i^+	D_i^-
A1	2.59329177	3.22711725
A2	3.22711725	2.59329177
A3	2.14451373	2.20575657

TABLE IX. FINAL SCORE OF TOPSIS

Code/Criteria	Final Score	Rank
A1	0.64710058	1
A2	0.35289942	3
A3	0.59624185	2

TABLE X. COMPARISON OF TOPSIS AND SAW

Code/Criteria	Score		Rank	
	SAW	TOPSIS	SAW	TOPSIS
A1	0.915	0.647100577	2	1
A2	0.81	0.352899423	3	3
A3	0.929	0.596241848	1	2

In Table X, a comparison is made between the SAW method in previous studies and the use of the TOPSIS method in this study. Things that are compared in the form of final scores and ranking results. The score obtained using the SAW method is greater than TOPSIS. Then, the ranking of alternative decisions is different. In the first SAW ranking, the alternative decision is A3 or the Samsung Galaxy A20, while using the TOPSIS method, the highest value is obtained, namely the alternative decision A1 or Realmi Narzo 10A.

VIII. CONCLUSION

This research generates a proposed framework for decision making based on sentiment analysis. This framework is a development from previous research where there is a change in the Sentiment Analysis Engine section using a Word2Vec document representation for feature extraction. In addition, preference modeling that previously used SAW became TOPSIS. The use of TOPSIS modeling has a more detailed calculation because it separates the calculations for positive and negative ideal solutions. This results in the final value of the alternative decision being lower than using SAW. This also results in differences in the ranking of alternative decisions.

ACKNOWLEDGMENT

We would like to thank all members of the Universitas Nusantara PGRI Kediri and Universitas Amikom Yogyakarta who have supported the implementation of this research. Besides that, we would like to thank a lot for the ICOIACT 2021 committees for big contribution in providing publication media for our research.

REFERENCES

[1] R. Wagh, "Survey on Sentiment Analysis using Twitter Dataset," *2018 Second Int. Conf. Electron. Commun. Aerosp. Technol.*, no. Iceca, pp. 208–211, 2018.

[2] J. I. Peláez, E. A. Martínez, and L. G. Vargas, "Decision making in social media with consistent data," *Knowledge-Based Syst.*, vol. 172, pp. 33–41, 2019.

[3] E. Daniati and H. Utama, "Decision Making Framework Based On Sentiment Analysis in Twitter Using SAW and Machine Learning Approach," in *2020 3rd International Conference on Information and Communications Technology (ICOIACT)*, 2020, pp. 218–222.

[4] P. Ducange, M. Fazzolari, M. Petrocchi, and M. Vecchio, "An effective Decision Support System for social media listening based on cross-source sentiment analysis models," *Eng. Appl. Artif. Intell.*, vol. 78, no. October 2018, pp. 71–85, 2019.

[5] A. Shukla, P. Agarwal, R. S. Rana, and R. Purohit, "Applications of TOPSIS Algorithm on various Manufacturing Processes: A Review," *Mater. Today Proc.*, vol. 4, no. 4, pp. 5320–5329, 2017.

[6] D. Antonakaki, P. Fragopoulou, and S. Ioannidis, "A survey of Twitter research: Data model, graph structure, sentiment analysis and attacks," *Expert Syst. Appl.*, vol. 164, no. February 2020, p. 114006, 2021.

[7] M. Soleymani, D. Garcia, B. Jou, B. Schuller, S. F. Chang, and M. Pantic, "A survey of multimodal sentiment analysis," *Image Vis. Comput.*, vol. 65, pp. 3–14, 2017.

[8] J. Chanwijit, W. Lomwongpaiboon, O. Dowjam, and P. Tangworakitthaworn, "Decision Support System for Targeting Higher Education," in *Proceedings of the 2016 5th ICT International Student Project Conference, ICT-ISPC 2016*, 2016, pp. 154–157.

[9] E. Walling and C. Vaneeckhaute, "Developing successful environmental decision support systems: Challenges and best practices," *J. Environ. Manage.*, vol. 264, no. April, 2020.

[10] J. Seyedmohammadi, F. Sarmadian, A. A. Jafarzadeh, M. A. Ghorbani, and F. Shahbazi, "Application of SAW, TOPSIS and fuzzy TOPSIS models in cultivation priority planning for maize, rapeseed and soybean crops," *Geoderma*, vol. 310, no. November 2016, pp. 178–190, 2018.

[11] C. G. Thomas, *Research Methodology and Scientific Writing*, Second. Kerala, India: Springer, 2021.

[12] V. Vargas-Calderón and J. E. Camargo, "Characterization of citizens using word2vec and latent topic analysis in a large set of tweets," *Cities*, vol. 92, no. 62, pp. 187–196, 2019.