Measuring User Satisfaction of Educational Service Applications Using Text Mining and Multicriteria Decision-Making Approach

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Abstract—Rapid growth of educational technology services today means that there are more applications in the market. Users may find it hard to choose the most suitable application, so they look for references. Experience shared in the form of text reviews and numerical rating can provide references. Text reviews are particularly specific and so they can provide insights to user satisfaction. In this study, we use text mining and multicriteria decision-making approach to measure the user satisfaction. The data is crawled and collected from seven educational applications: Coursera, edX, Khan Academy, LinkedIn Learning, Quipper, Socratic and Udemy. Nine attributes are used to measure the user reviews according to quality model of e-learning systems. The result is in favor of Khan Academy, while Quipper is ranked the lowest. The v-values used range between 0 and 1 and what is unique is that the rank of Khan Academy and Quipper are not affected by v-value while the ranks of the other applications are. It indicates that Khan Academy has high user satisfaction in terms of utility and low complaint from individuals. Quipper shows the opposite.

Keywords—educational application service, information and communication technology, multi criteria decision making, sentiment analysis, technology education

1 Introduction

The number of applications (apps) downloadable via mobile phone or website is increasing rapidly, and so is the number of users. In 2021, the number of available apps has reached 4.41 million [1]. Two of the major application platforms nowadays are Google Play and App Store, with categories of app offered including art/design, business, education, health, sports, weather, etc. [2]. During the COVID-19 outbreak, certain apps reached the greatest number of downloads, including the educational service apps. The downloads started in the first quarter of 2020, when the COVID-19 outbreak started in Indonesia and continued until the downloads reached 466 million on Google Play by the fourth quarter of 2020. Google Play is indeed the platform with the highest

reported educational app downloads in that year [3]. The surging downloads of educational services are most likely a result of work and study from home.

With the large number of apps available for download, users may find it difficult to choose which apps are reliable and suitable for their needs. There are a lot of available educational application services such as Coursera, edX, Khan Academy, LinkedIn Learning, Quipper, Socratic and Udemy, downloadable anywhere and anytime. These apps help students to create effective collaboration with teachers and other learners outside class. It also comes with a strong content management system and various course materials. The app developers collaborate with many educational institutions so that users will get relevant and up-to-date materials.

Prior to download, users often read the reviews from other users to decide whether an app is suitable for them. The reviews depict the user experience [4] that could be more comprehensive than numeric rating reviews. These text-based reviews provide valuable information both for users and developers. In a developer's perspective, it could help them to improve application standards, whereas in a user's perspective, it can help them to make decision.

Users voluntarily write genuine reviews based on their experience concerning various aspects of an app. However, due to the high volume, it is not possible for users to read all the reviews. Therefore, they often see the overall rating from numeric reviews although it will not provide specific information about an app's quality. From the problems mentioned, it is necessary to develop a method to help users in analyzing reviews. Past studies have focused on the analyses of consumer products via reviews to develop a decision-making system [5-10]. The current study aims to extend the body of literature by examining user reviews of educational apps.

Multi criteria decision-making (MCDM) is a collection of decision-making algorithms that help people to decide according to their preferences [11]. MCDM is used when there more than one alternative or more than one conflicting criterion. It is often used when dealing with a complex problem because it splits a complex problem into smaller components. It is widely used in various areas such as transportation [12], strategic management [13], supply chain management [14], production management [15], and tourism [16-17]. Several methods of MCDM are TOPSIS, ELECTRE, VIKOR, AHP, etc. Among those MCDM methods, VIKOR is one of the best ranking methods for this study because it examines the ranking process and considers identical rank for some alternatives [18].

The proposed method in this study consists of three stages: collecting and pre-processing text reviews, text-mining lexical attributes, and measuring user satisfaction towards educational application services from the lexical attributes. Seven educational service apps were included in the current study. First, we collected the most recent data crawled from the apps. The raw data collected were pre-processed to prepare them for text-mining and sentiment analysis. Then, we mined the lexical attributes and used a sentiment analysis to determine the polarity of each word. The negative and positive sentiments were scored to measure user satisfaction of each app. Finally, we weighed the scores by using VIKOR.

The remain section of this study are organized as follows. The proposed method and basic theory of method are introduced in Section 2. Then we integrated and explained

in detail process steps therein such as data collection, data pre-processing, text mining, sentiment analysis and MCDM-VIKOR in Section 3. In Section 4, we presented the results in the form of table and chart, then explain the results. Finally, Section 5 concludes the paper.

2 Method

The proposed method can be seen in Figure 1. The data were collected from Google Play Store website. The reviews were crawled from seven educational service apps. Then, the data were pre-processed through a series of stages to make them ready for mining and analyzis. In the mining and analysis, the output is keyword vectors. These are prepared for the next stage where vectors are turned into a decision matrix. In the final stage, VIKOR approach as part of MCDM is run through the data.
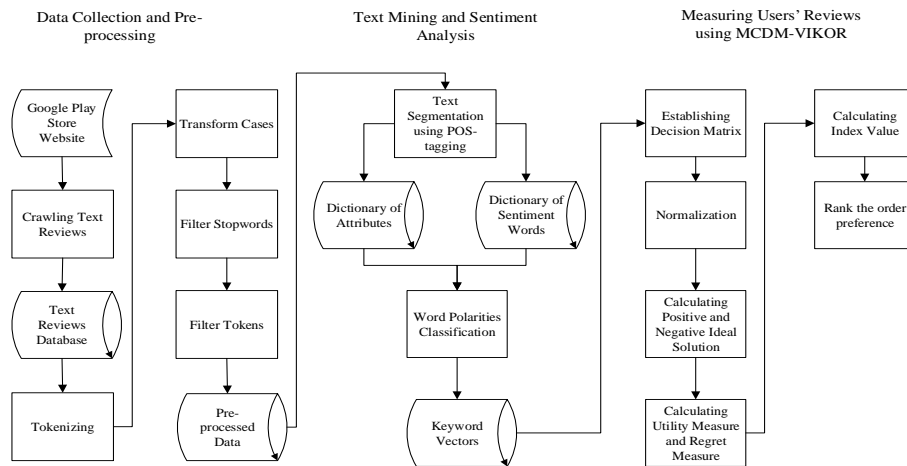

Fig. 1. Proposed Method

2.1 Data collection

The data were collected by considering similarities in features. Common aspects were extracted from the review data and used to measure and compare user satisfaction. The reviews about Coursera, edX, Khan Academy, LinkedIn Learning, Quipper, Socratic, and Udemy were extracted from Google Play website. 200 reviews from each application were collected so the total of the data used in this study are 1,400 reviews. The example of online review from each educational app can be seen in Table 1.
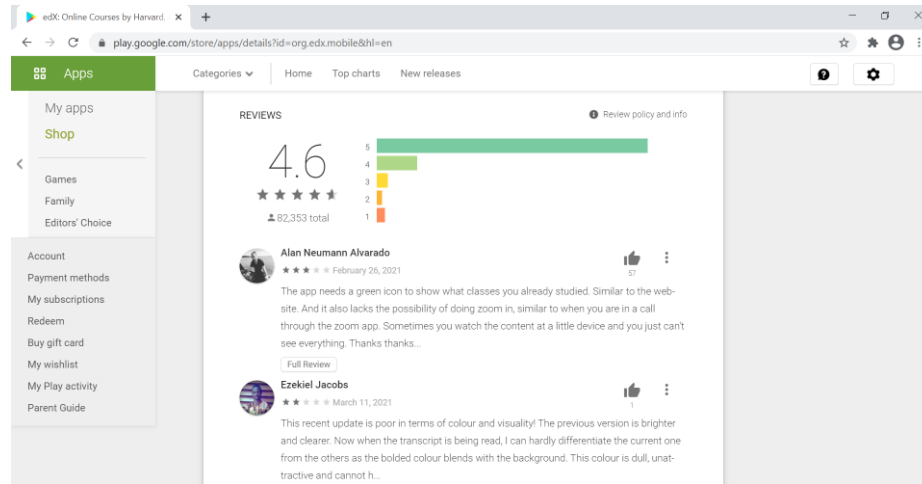
Fig. 2. Users' Reviews from Google Play Website

Table 1. Online review examples

Educational services application	Review	Rate
Coursera	"The best thing about this app is, it just shattered the brick-and-mortar concept of quality education. Thank you everyone associated with Coursera."	5
edX	"This is so good. I just watch one video, and I think this application is made by a lot of people than want to share their knowledge. For free. May God bless you all"	5
Khan Academy	"Great app! Exactly what I was looking for, much needed refresher of knowledge and great explanation and examples specially for math's, which is not my strongest subject. Very grateful for the team sharing their knowledge and making this app available"	5
LinkedIn Learning	"Just started using the app. Love the minimal UI design. Good courses subject to your requirements."	4
Quipper	"I can't find or join in the class. I put the code correctly and the given code is doubled checked by our teacher but still cannot join there. Can you please help"	2
Socratic	"Very helpful app especially for students like I am. But I wish you guys could add a search history feature where I can see my last searched questions. Quite useful"	3
Udemy	"Very handy overall, but when viewing PC based courses, would be handy to be able to zoom in to the video as its sometimes difficult to see all the writing on screen"	4

2.2 Data pre-processing

The data pre-processing transforms unformatted data into understandable formatted data to be processed in the next stages. This starts from data cleaning to remove irrelevant or noisy data. Noisy data are meaningless and cannot be interpreted because there

are entry errors or faulty collection. The second stage is data transformation which includes tokenizing, case folding, stop words filtering and stemming. The result from data pre-processing is a collection of stem words that are free from stop words and irrelevant characters or strings.
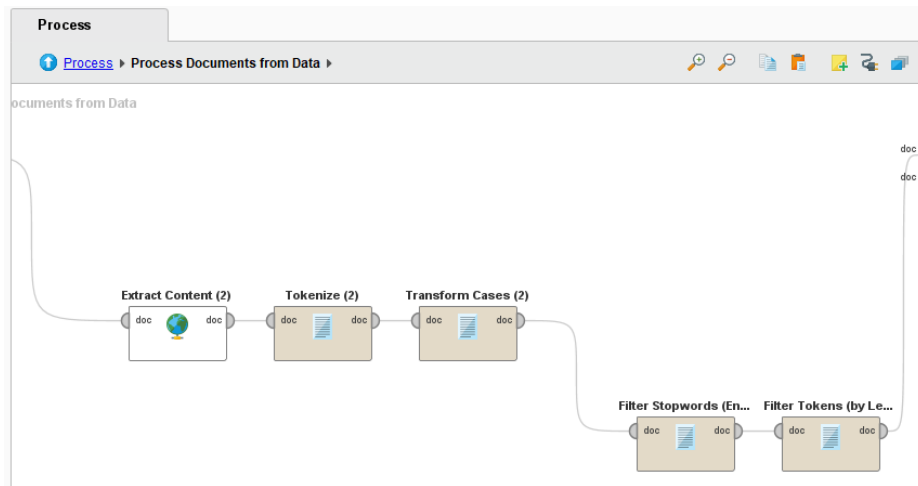

Fig. 3. Data Pre-processing using RapidMiner

2.3 Text mining

The text-mining process in the current study consists text segmentation, summary extraction, keyword identification, topic detection, term clustering and document categorization. The aim is to compile dictionaries that consist of two types of words: a dictionary of attributes and a dictionary of sentiment words, which is different from the method proposed by [19]. They considered attribute and sentiment words as pairs. They paired attribute and sentiment to determine the polarities. If a sentiment word is labelled positive then its pair word is labelled as positive too, and vice versa. In the current study, this is not the case because each word has been determined its label. It is not based on its pairs.

Subsequently, the collection of stem words from the data pre-processing were classified into their part-of-speech (POS) tagging. Ireland and Liu [20] divided several POS-tags. POS-taggers used in this study is Stanford POS-tagger [21]. This POS tagger identifies adjective, adverb, noun, numeral, and verb. The dictionary of attributes is composed of noun phrases only while the rest went to dictionary of sentiment words.

Nine categories were selected to measure user satisfaction, as shown in Table 2. The categories are determined based on functionality, reliability, and usability [22]. After both dictionaries were developed then the words from sentiment words dictionary were classified into five groups of polarities: strong positive; positive; neutral; negative; strong negative. The spectrum of polarity usually consists of three types: positive, neutral, and negative. Dina [23] and Prastyo et al. [24] divided the polarity into three types.

They applied sentiment analysis to determine the experience of hotel customers based on the most frequently mentioned words in its reviews. In this study we used five types of polarity so the result could be more specific and accurate. The polarity values are between 2 and -2 where strong positive = 2; positive = 1; neutral = 0; negative = -1; strong negative = -2. Finally, if there were no sentiment words appear then the polarity value was set as 0. The polarity value was used to construct keyword vectors of the user reviews. These were obtained by multiplying the occurrence attributes and the polarity value of sentiment words from the review data.

Table 2. Category and description

Category	Description
Download (C1)	Ease of download
Image (C2)	Quality of image displayed
Video (C3)	Quality of video displayed
Cost (C4)	Payment requirement before it can be used
Assignment (C5)	A task or piece of work assigned to users as part of a course
Content (C6)	Any informational material needed for learning
Course (C7)	A series of lessons or lectures on a particular subject
Exam (C8)	A formal test that users take to check their comprehension of a particular subject, or to obtain a qualification
Teacher (C9)	A person who teaches or instructs

2.4 Measuring user satisfaction using vlseKriterijumska optimizacija I kompromisno resenje (VIKOR)

VIKOR stands for vlseKriterijumska optimizacija I kompromisno resenje. It is Serbian and was first established by Opricovic [25] as one of multicriteria decision making (MCDM) approaches. This method helps to solve a problem by considering the multicriteria [26]. It uses multicriteria ranking index to compare the closeness of each criterion so that the ideal alternative is obtained. A ranking index is obtained by calculating the maximum group utility (S_j) and minimum individual regret (R_j) [27]. There are several steps to be completed using VIKOR, as follows:

Establishing the decision matrix. The decision matrix is formed from the keyword vectors or it could simply be defined as the multiplication of attributes occurrence and polarity value for each attribute. Then, the number of attribute instances are counted for each category. The structure of decision matrix can be illustrated as follows:

$$X = \begin{matrix} A_1 \\ A_i \\ A_m \end{matrix} \begin{bmatrix} SN_{11} & SN_{1j} & SN_{1n} \\ SN_{i1} & SN_{ij} & SN_{in} \\ SN_{m1} & SN_{mj} & SN_{mn} \end{bmatrix}$$

where:
A_i : *i*-th alternative,
SN_{ij} : the value of *j*-th aspect for *i*-th alternative.

Step 2: Calculating the normalized values and putting them into a decision matrix

The attributes occurrence (x) from each category from Step 1 is normalized to a value between 0 and 1. The formulation for normalization is shown in (1). The weighting scheme was applied to the data to measure the weight of each category (w_k) and it is calculated using (2) where n_k (d) = number of times k-th category occurs in document d,

$$x^* = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

$$w_k = \frac{n_k\ (d)}{\sum_{k=1}^{m} n_k(d)} \tag{2}$$

Step 3: Calculating the best f_j^* and worst f_j^- of all criteria

The positive (f_j^*) and negative (f_j^-) ideal solution is obtained using (3).

$$f_j^* = \max_i f_{i,j} \text{ and } f_j^- = \min_i f_{i,j} \tag{3}$$

Step 4: Calculating new decision matrix with the weight (w_j)

The formula to assign the weight (w_j) for a new decision matrix is written in (4).

$$\frac{w_j(f_j^* - f_{ij})}{f_j^* - f_{ij}^-} \tag{4}$$

Step 5: Calculating the values of the group utility (S_i) and individual regret (R_i)

The calculation of utility measure (S_i) and regret measure (R_i) are done using (5) and (6) where w_j is the weight of the category.

$$S_i = \sum_{i=1}^{n} \frac{w_j(f_j^* - f_{ij})}{f_j^* - f_{ij}^-} \tag{5}$$

$$R_i = \max \left[\frac{w_j(f_j^* - f_{ij})}{f_j^* - f_{ij}^-} \right] \tag{6}$$

Step 6: Calculating the index value (Q_i) by using (7),

where S^* = maximum value of S_i; S^- = minimum value of S_i; R^* = maximum value of R_i; R^- = minimum value of R_i; v = index weight value.

$$Q_i = v\left[\frac{S_i - S^*}{S^- - S^*}\right] + (1 - v)\left[\frac{R_i - R^*}{R^- - R^*}\right] \tag{7}$$

Step 7: Ranking the order preference of index value (Qi)

The smallest the index value, the better the solution is.

3   Results and discussion

Table 3 displays the calculated score for all the categories (C_n) as described in Table 2. There are positive and negative values for the calculated scores. If the score is negative, then the number of negative polarities is bigger than the positive polarity in those categories. The last row shows the number of term instances in each category. Table 4 is generated from Table 3; the normalized score is obtained by applying formula in (1) while the weight from the last row is calculated by using (2).

Table 3. Calculated Scores

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Coursera	-182	56	-222	-37	-48	-24	408	-88	154
Edx	0	0	80	0	0	8	332	0	0
Khan Academy	203	0	638	218	124	160	1253	267	310
Linkedin Learning	30	0	-53	0	499	802	0	36	0
Quipper	69	-15	36	-3	52	35	-269	65	-103
Socratic	0	679	0	0	263	104	265	224	0
Udemy	0	0	-225	-147	0	120	803	0	16
Term presence	53	75	216	38	47	175	487	64	51

Table 4. Normalized Scores

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Coursera	0.057	0.214	0.031	0.152	0.145	0.161	0.445	0.119	0.278
Edx	0.177	0.177	0.229	0.177	0.177	0.182	0.395	0.177	0.177
Khan Academy	0.310	0.177	0.596	0.320	0.258	0.282	1.000	0.352	0.380
Linkedin Learning	0.196	0.177	0.142	0.177	0.505	0.704	0.177	0.200	0.177
Quipper	0.222	0.167	0.200	0.175	0.211	0.200	0.000	0.219	0.109
Socratic	0.177	0.623	0.177	0.177	0.350	0.245	0.351	0.324	0.177
Udemy	0.177	0.177	0.029	0.080	0.177	0.256	0.704	0.177	0.187
Weight	0.044	0.062	0.179	0.032	0.039	0.145	0.404	0.053	0.042

Table 5. Positive Ideal Solution

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
fj*	0.310	0.623	0.596	0.320	0.505	0.704	1.000	0.352	0.380
fj-	0.057	0.167	0.029	0.080	0.145	0.161	0.000	0.119	0.109

Equation (3) was applied to determine the positive ideal solution (f_j^*) and negative ideal solution (f_j^-). The positive ideal solution was obtained by comparing the normalized value in Table 4. The maximum value is regarded as a positive ideal solution (f_j^*) and the minimum value is a negative ideal solution (f_j^-). Both values are presented in Table 5. Next, Table 6 shows the results of the new decision matrix after multiplying the normalized values by the weight.

The index value (Q_i) determines the rank of each app based on the calculation formula in (7). The lowest index value shows the highest user satisfaction of various criteria. The Q_i value involves the calculation of utility measure (S_i) and regret measure (R_i). Equation (5) and (6) are used to calculate both values. From Table 6, it can be seen that the specific criteria that need to be improved most is course (C_7), video (C_3) and content (C_6) with reference to their R_i values in Table 7.

Table 6. Normalized Decision Matrix with Weight

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Coursera	0.044	0.056	0.178	0.022	0.039	0.145	0.224	0.053	0.016
Edx	0.023	0.061	0.116	0.019	0.036	0.139	0.244	0.040	0.032
Khan Academy	0.000	0.061	0.000	0.000	0.027	0.113	0.000	0.000	0.000
Linkedin Learning	0.020	0.061	0.143	0.019	0.000	0.000	0.332	0.035	0.032
Quipper	0.015	0.062	0.125	0.019	0.032	0.135	0.404	0.030	0.042
Socratic	0.023	0.000	0.132	0.019	0.017	0.123	0.262	0.006	0.032
Udemy	0.023	0.061	0.179	0.032	0.036	0.120	0.119	0.040	0.030

From the results given in Table 7, the sensitivity analysis was conducted to rank the highest and the lowest index values of seven educational apps. The *v*-value range from 0 to 1. Figure 4 shows that the ranking of Khan Academy and Quipper are not affected by the *v*-value. Khan Academy was ranked as the number one while Quipper was ranked as the last. It means that Khan Academy has high user satisfaction in terms of maximum group utility and minimum individual regret while Quipper is the opposite. Meanwhile, the rank of Coursera and Udemy are lower when the *v*-value is increased. If Coursera and Udemy focuses on minimum individual regret, then both apps will have higher user satisfaction. On the other hand, LinkedIn Learning and Socratic's rank are higher when *v*-value is increased. It means that the user satisfaction of LinkedIn Learning and Socratic score will be higher if the maximum group utility is increased.

Table 7. Q values

|	S_i	R_i	Q_i										
			v=0	*v=0.1*	*v=0.2*	*v=0.3*	*v=0.4*	*v=0.5*	*v=0.6*	*v=0.7*	*v=0.8*	*v=0.9*	*v=1*
Coursera	0.778	0.224	0.383	0.431	0.480	0.529	0.577	0.626	0.675	0.723	0.772	0.821	0.869
Edx	0.710	0.244	0.452	0.484	0.515	0.547	0.578	0.610	0.641	0.673	0.704	0.736	0.767
Khan Academy	0.200	0.113	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Linkedin Learning	0.642	0.332	0.755	0.746	0.737	0.728	0.719	0.710	0.701	0.692	0.682	0.673	0.664
Quipper	0.864	0.404	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Socratic	0.614	0.262	0.513	0.524	0.535	0.546	0.557	0.568	0.579	0.590	0.601	0.612	0.623
Udemy	0.639	0.179	0.228	0.271	0.315	0.358	0.401	0.445	0.488	0.531	0.575	0.618	0.661
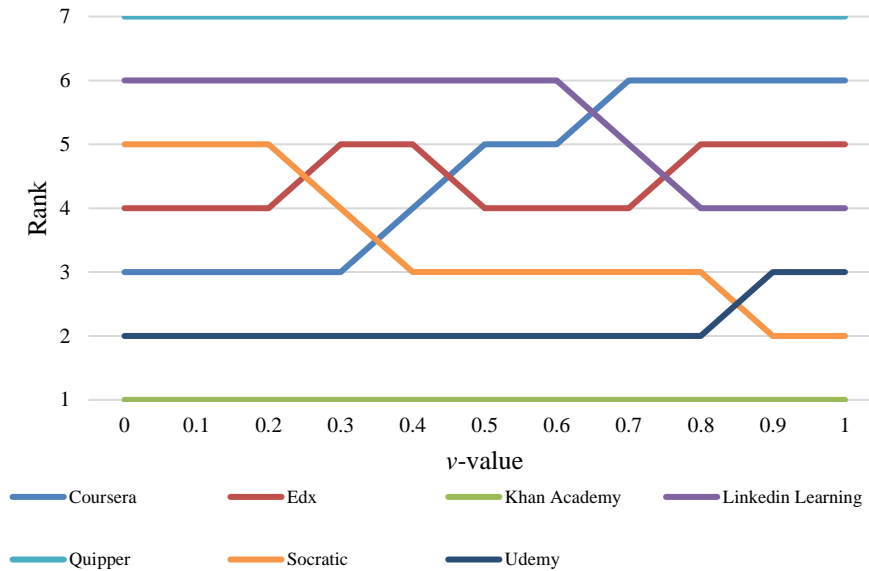
Fig. 4. Sensitivity Analysis

However, this study has several limitations such as the number of apps covered as case studies are only seven. Increasing the number of apps will improve the robustness of this study. The total number of reviews which are crawled from the website is only 1,400. Considering the high volume of reviews online, the number of text reviews could be increased in order to capture the trends more accurately. In addition, future research will also benefit from combining both star rating reviews and text reviews to generate a more holistic measurement system. The categories selected in the current study are based on ISO 9126 as quality model for the e-learning systems. It could be compared with other quality models as well. Last, the MCDM approach used in this study is only VIKOR. Future study needs to be conducted to do a comparative analysis involving other MCDM methods in order to corroborate the findings.

4   Conclusion

This study proposes a framework for measuring user satisfaction of educational apps based on the user reviews. The data used in this study is actual user reviews. Text mining is used to extract lexical attributes from the reviews and a sentiment analysis is conducted to determine the word polarity. After doing text mining and sentiment analysis, then the word vector was measured using an MCDM algorithm, namely VIKOR. The weight of each criterion in VIKOR is obtained by calculating the term occurrence. It is used to help reducing subjectivity in the evaluation. From the seven educational apps, it can be concluded that Khan Academy shows the highest satisfaction and Quip-

per shows the lowest. The result shows that user satisfaction is also influenced by maximum group utility and individual regret. The future study should be conducted using another MCDM method to validate the result. The number of the data crawled should be added to improve directory of attribute and sentiment word. The categories also should be wider than nine categories in this study.

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