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Identification of Customer Needs for Laptop in a Product Reviews using the Aspect-Based Sentiment Analysis Method

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Abstract: The increasingly widespread use of the internet allows companies to gain insights regarding product development. Online reviews can provide an overview of how customers need a product, and this can help companies to understand what customers like and dislike about their products. This paper proposes a methodology for identifying consumer needs by analysing online reviews using the lexicon-based method and topic modeling with Non-negative Matrix Factorization (NMF). The main idea of this paper is to translate the results of aspect-based sentiment analysis into consumer needs with its priority ranking. The methodology is applied in an online review of a laptop product. Based on the study results, it is shown that the observed features based on customer reviews are battery, storage, screen, price, performance, keyboard, and design, with each topic having overall positive sentiment. Based on the topics and their sentiment, the prioritized needs are good screen strength, a fast and responsive processor, and responsive keyboard keys.

Keywords: Customer Needs, Aspect-based Sentiment Analysis, Non-negative Matrix Factorization (NMF), Lexicon-based Approach

1. Introduction

The Fourth Industrial Revolution presents technology that can improve the quality of life, where people can meet their needs with more efficient and productive production systems and digital platforms [1]. Production systems no longer require manpower, and machines can operate autonomously, hence, smart systems. The quality and quantity of manufacturing are increased quickly with the emergence of smart systems [2]. This affects companies in delivering their designed products because competition becomes tighter along with the advancement of this technology. In the current competitiveness, companies' success depends on how they transform obtained information innovatively into valuable products for customers in a faster way and at lower costs [3]. Companies need to understand what customer needs and provide effective and improved products in designing their products [4]. The internet can help companies in finding information on what their customer needs.

Internet is the backbone of industry 4.0, where all things are developed and implemented around IoT-related technologies [1]. The rapid development in IoT-related technology encourages people to use the internet daily. By January 2021, the number of active internet users has reached 4.66 billion [5], and it is estimated that by 2022 the data size will reach 94 zettabytes [6]. Any data that is available on the internet, such as, online reviews may be useful to find information on a customer's needs regarding a product faster. Customer needs are conventionally obtained by conducting interviews, focus groups, observing the products used [7] or questionnaires [8]. However, this method requires a relatively high cost, effort, and time [9]. A new method is needed to analyze customer needs based on a large volume of product online reviews in a short time.

Product online reviews provide textual information regarding customer concerns about the product and can give companies a general idea of how to improve products [4]. In recent years, online reviews have been widely used in various research, for instance, to identify the relationship between reviews and sales ranks [10], to analyze user interaction [11], and to analyze the product aspect sentiment [12], [13]. These studies used Natural Language Processing (NLP) tools to extract textual information from online reviews with promising outcomes. This information can help companies understand their product better from the customer's point of view.

One of the major tasks of NLP is sentiment analysis. Analyzing sentiments of the products' aspects can help know customer likes and dislikes on products' aspects. There is three level of sentiment analysis, and one of the commonly used is aspect-level. Aspect-based sentiment analysis uses text-based reviews to detect the degree of polarization of an aspect. The main idea of aspect-based sentiment analysis is to study the words that contain opinions and their target, then compare them to the lexicons [14].

In general, aspect-based sentiment analysis research focus on the method's performance rather than providing design-relevant insights [12], [15], [16], [17]. This paper

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provides a different approach, where the results of aspect-based sentiment analysis are then translated to design insights. Online reviews are used to find product features and opinions and translate them into customer needs using aspect-based sentiment analysis and topic modeling with the Non-negative Matrix Factorization (NMF) method. ASUS products are used as a case study as the laptop company experienced the highest market share decline in 2019 [18]. The results of this paper are customer needs relevant to the product features and its priority ranking that can help the early-stage process of ASUS's product development.

This method may not provide factors that cause the failure or success. However, it may deliver information on how the product is in the eyes of the public or customers and helps to identify customer needs. Identifying product opportunities and conceptual ideas based on customer needs is crucial in product development [19]. It plays a leading role in creating concept designs, product specifications, and overall product development [7]. Companies can use the proposed method to identify features needs that are important for customers for further product development consideration.

The rest of the paper proceeds as follows: Section 2 presents a literature review of the existing related research and a brief explanation of sentiment analysis and topic modeling. An overview of the proposed methodology is provided in Section 3. Sections 4 and 5 provide results and discussion of the proposed methodology. Conclusion and future work are presented in Section 6.

2. Literature Review

Sentiment analysis or Opinion Mining is a study that analyzes people's opinions, sentiments and emotions towards attributes of products, services, organizations, or topics and can be applied to various possible domains such as product, service, healthcare, financial services, social events, and political election [14]. There are several approaches in sentiment analysis; the most commonly used are the machine learning approach and lexicon-based approach. The lexicon-based approach uses a sentiment lexicon that consists of information about positive and negative words and phrases [20].

A suitable lexicon for the laptop domain is needed to perform a lexicon-based approach. Hu and Liu's lexicon [21] was created by extracting opinion words based on the frequent features and semantic orientations of the opinion words. MPQA Subjectivity lexicon used a two-step process, classifying each phrase by neutral or polar and disambiguating polar ones by their contextual polarity [22]. Mohammad and Turney [23] used crowdsourcing to create NRC Sentiment and Emotion Lexicons on Macquarie Thesaurus, WordNet Affect Lexicon, and General Inquirer [24]. Khoo and Johnkan [24] evaluated the three lexicons and recommended Hu and Liu's lexicon for product reviews text.

There are three sentiment analysis levels: document-level, sentence-level, and aspect-level. Aspect-level is more desirable to have a fine-grained sentiment analysis. A study by Wu, Zhang, Huang, and Wu [25] used the language rule method by using phrase dependency parsing to extract product features and opinion words on 11 products customer reviews. Phrases categorized as nouns or verb phrases are selected as product features candidates. In contrast, the candidate for opinion words is based on a dictionary by Wilson, Wiebe, Hoffman [22]. Zhang, Lu, and Liu [26] proposed a similar methodology using aspect-based sentiment analysis to identify customers' preferences for hotel attributes based on Chinese online reviews.

Mubarok, Adiwijaya, and Aldhi [27] provide an aspect-based sentiment analysis method based on Naive Bayes aspect sentiment classification with part-of-speech (POS) tagging and Chi-Square feature selection. POS tagging is used to classify the aspect and opinion words based on the tags. Every word with tags of JJ, JJR, JJS, RB, RBR, and RBS was considered the aspect and NN, NNS, NP, and NPS tags were considered opinion words. The method proposed in [25], [26], [27] required labeled data to process the sentiment analysis. Labeled data can be a limitation in machine learning since there is often insufficient training data [28].

Jardim and Mora [29] combined sentiment analysis and automated clustering to cluster users based on the sentiment polarities of user reviews. Lexicon-based sentiment analysis is adapted in the methodology using TextBlob. The results show a high accuracy for sentiment classification and user segmentation. Still, there is a limitation due to the incapacity of the algorithm to detect negation words such as a negative sentiment "do not agree".

Aspect-based sentiment analysis can be combined with topic modeling. Topic modeling is an algorithm to discover the main theme within a large and unstructured document [30]. Topic modeling uses mathematical and statistical modeling such as matrix factorization and Singular Value Decomposition (SVD) to clusters that form the main theme [31]. Latent Dirichlet Allocation (LDA) is widely used in topic modeling research. Jabr, Khao, Cheng, and Srivastava [32] used LDA to generate product-specific topics as aspects from 1000 products listed on Amazon. The topic association is measured by cosine similarity between the sentence and the topics are used by Singhal [33]. It provides a better result in separating different aspects of a sentence and their sentiments. They performed a lexicon-based sentiment analysis with the NRC emotion dictionary and reflected the positive and negative sentiments as satisfaction.

A similar study by Yiran and Srivastava [34] used LDA to cluster topics contained in mobile phone reviews. The topic then provides the aspect of sentence-level reviews and sentiment analysis by utilizing emoji sentiment score [35], domain-specific lexicon, and SentiWordNet. Sentiment weights are calculated by the sum of three previously stated lexicon scores. They set a threshold of a minimum of 20 words for the text length to eliminate short texts, as it was stated by Song, et al. [36] that LDA model does not work well on short text. Short texts only contain a few meaningful keywords so it is harder to capture information [37]. The summarization of related works can be seen in Table I.

Non-negative matrix factorization is a topic modeling method that can overcome the short text limitation in LDA. An experiment by Chen, Zhang, Liu, Ye, and Lin [38] shows that NMF performs better in processing short text than LDA. NMF is a method of solving or parsing a matrix with a non-negative matrix constraint [41]. As illustrated in Figure 1, there is an X matrix with size m × n with $x_{ij} > 0$, which will be broken down into two non-negative matrices W and H, so that [41]:

$$X \approx W \times H \tag{1}$$

A cost function definition that can quantify the quality of the approximations is needed. This cost function can measure the distance between two non-negative matrices A and B, and the measurement that used is the square of the Euclidean distance between A and B [41].

$$\| A - B \|^2 = \sum_{ij} (A_{ij} - B_{ij})^2 \tag{2}$$

Based on Equation 2 the cost function for the approximation problem can be written as follows [41]:

$$f(W, H) = \| X - WH \|^2 = \sum_{ij} (x_{ij} - wh_{ij})^2 \tag{3}$$

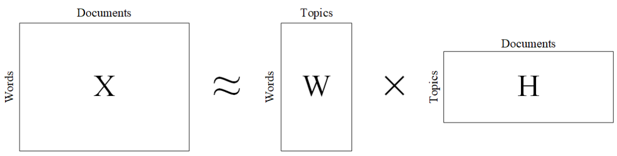


Figure 1. Non-negative Matrix Factorization model

A few studies have used NMF to extract aspects in reviews but are limited to Restaurant or Hotel domain [39], [40]. This paper aims to apply aspect-based sentiment analysis combined with NMF focused on the laptop domain. Aspect-based sentiment analysis is performed using the dependency parsing method to extract the aspect and sentiment of each review sentence. NMF to discover the main topics and its keywords in the reviews and assign each review with topics based on the approximation value in matrix H. Each review will be classified based on the topic and sentiments to provide an easier way to translate customer needs.

3. Methodology

The data used is online review data for a laptop on Amazon in English. Data were gathered using the scraping method with Selenium. In addition, several other laptops reviews that were quite similar were gathered. This was intended to obtain a better topic modeling result. The proposed methodology is presented as a flowchart in Figure 2.

A. Topic Modeling

The purpose of topic modeling is to find out the topics/aspects discussed by the customer in product reviews. This stage includes preprocessing text, feature extraction, and topic modeling. In preprocessing text, the steps taken are tokenization, case folding, punctuation and numbers removal, lemmatization, stop words removal, and bigram identification.

- Tokenization divides text into token forms such as words, sentences, or others. Tokenization is done first by dividing the review text into single sentences and then dividing the text into words for the lemmatization process.
- Case folding is the process of changing the review sentence, which has capital letters to lowercase sentence
- Elimination of punctuation marks and numbers. Punctuation and numbers are often not helpful in identifying the topic in the review and should be removed.
- Lemmatization is the process of finding the basic form (called lemma) of a word. This normalization technique aims to form relationships between related words or word forms [42].
- Stop words removal remove common words that appear in large numbers and carry low information from a text [43]. The stop word that was used was based on the SpaCy package.
- Bigram identification identifies several aspects of the laptop which consists of 2 words: battery life, caps lock, and hard drive.

Feature extraction is how the significant features contained in the review are extracted. To obtain good classification results on topic modeling, feature extraction was conducted using the Term Frequency - Inverse Document Frequency (TF-IDF) method by scikit-learn. The TF-IDF formula by scikit-learn [44] used is as follows.

$$idf_t = \log\left(\frac{n}{df_t}\right) + 1 \tag{4}$$

$$tf - idf_{t,d} = tf_{t,d} \times idf_t \tag{5}$$

Where tf represents the number of words searched for in a document, n represents the total number of documents, dft represents the number of documents containing the term t. We set the parameter of minimum document frequency (min_df) as as 5 or 0,04%. The stop words parameter is also determined by using the same stop words library on preprocessing text with some additional universal words and is considered not to provide any assistance in identifying aspects of the laptop. Words and values are then stored in the document-term matrix.

The document-term matrix then becomes the input for the topic modeling process. After each topic is defined,

TABLE I. Summarization of Related Works

Ref	Objectives	Approach	Data Source
[24]	Comparing six sentiment lexicons for aspect opinion extraction	Lexicon-based (Hu & Liu, MPQA, General Inquirer, NRC, SO-CAL, WKWSCI)	Product reviews from 5 categories (apparels, electronics, kitchen and housewares, sports and outdoors, and video)
[25]	Extracting relations between product features and expressions of opinions	Machine learning with phrase dependecy parsing	11 products reviews belong to 5 categories (Diaper, Cell Phone, Digital Camera, DVD Player, and MP3 Player)
[26]	Identifying customer preferences	Lexicon based (HowNet) with dependency parsing	Hotel reviews
[27]	Aspect opinion and aspect sentiment polarity extraction	Machine learning (Naïve Bayes) with Chi-square feature selection	SemEval 2014 Task 4 - Restaurant Domain
[29]	Clustering users based on the sentiment polarities of user reviews	Lexicon-based (TextBlob) with clustering (K-Means)	Digital tourist platforms reviews
[32]	Aspect opinion extraction, aspect sentiment polarity extraction, and satisfaction measure	Lexicon-based (NRC emotion dictionary) with LDA topic modeling	1000 products reviews belong to 4 categories (Automotive, Grocery & Gourmet Food, Health & Personal Care, Home and Kitchen)
[34]	Identifying aspect category and aspect category sentiment polarity	Lexicon-based (emoji sentiment score, domain specific lexicon, and SentiWordNet) and LDA topic modeling	Mobile phones reviews
[38]	Comparing LDA and NMF based schemes for short text topic mining and develop improved models	Topic modeling with NMF and LDA	Short texts from Snippet, News, StackOverFlow, XinlangNews, TMNtitles
[39]	Aspect category extraction	Topic modeling with NMF and LDA	Restaurant reviews
[40]	Developing Weakly-Supervised Approach for Aspect Based Sentiment Analysis (WS4ABSA)	Lexicon-based (using a set of sentiment seed words) with NMF topic modeling	SemEval data sets: Restaurant and hotel reviews

the next step is to assign topics to each review. Several parameters must be defined, first the initialization and number of topics. The method used for the initialization is Non-negative Double Singular Value Decomposition (NNDSVD) to avoid results variety in each run. In addition, this method can also reduce the approximation error of the NMF algorithm [45].

B. Aspect-based Sentiment Analysis

The next step is aspect-based sentiment analysis. Aspect-based sentiment analysis in this study uses a lexicon-based approach. The lexicon used is the opinion lexicon from Hu and Liu [21]. The steps were pre-processing text, lexicon extraction, aspect identification and aspect sentiment analysis. In pre-processing text, the text only goes through the case folding process, tokenization by dividing the review text into single sentences, and punctuation and numbers removal.

The next step is to collect negative and positive words with lexicon extraction. These two types of words are compiled into one whole collection of opinion words. A model is designed based on the dependency parsing method to identify aspects and analyze the sentiments. This method tokenizes text into words and provides word classes and syntactic labels. The model reads sentences and analyses sentiments by looking at the opinion words contained in the sentence. If the opinion word is included in the opinion word list, then the aspect of the opinion word is analyzed. There are five criteria designed to inspect aspects as shown in Algorithm 1. This criterion is the adoption of the ones used in the previous study [46].

After the aspects and opinions are identified, each review gets a score according to its opinion. Positive opinion words have a score of 1, and negative opinion words have a score of -1. If in one sentence there are only 2 opinion words, the score obtained is 2. If there is one negative and positive opinion word, the score is 0.

C. Customer Needs Identification

The results of the two stages are combined and classified into aspects with each sentiment, such as battery negative, battery positive, and battery neutral. Neutral classification is a classification where reviews score 0, or there is no pair of aspects and sentiment identified.

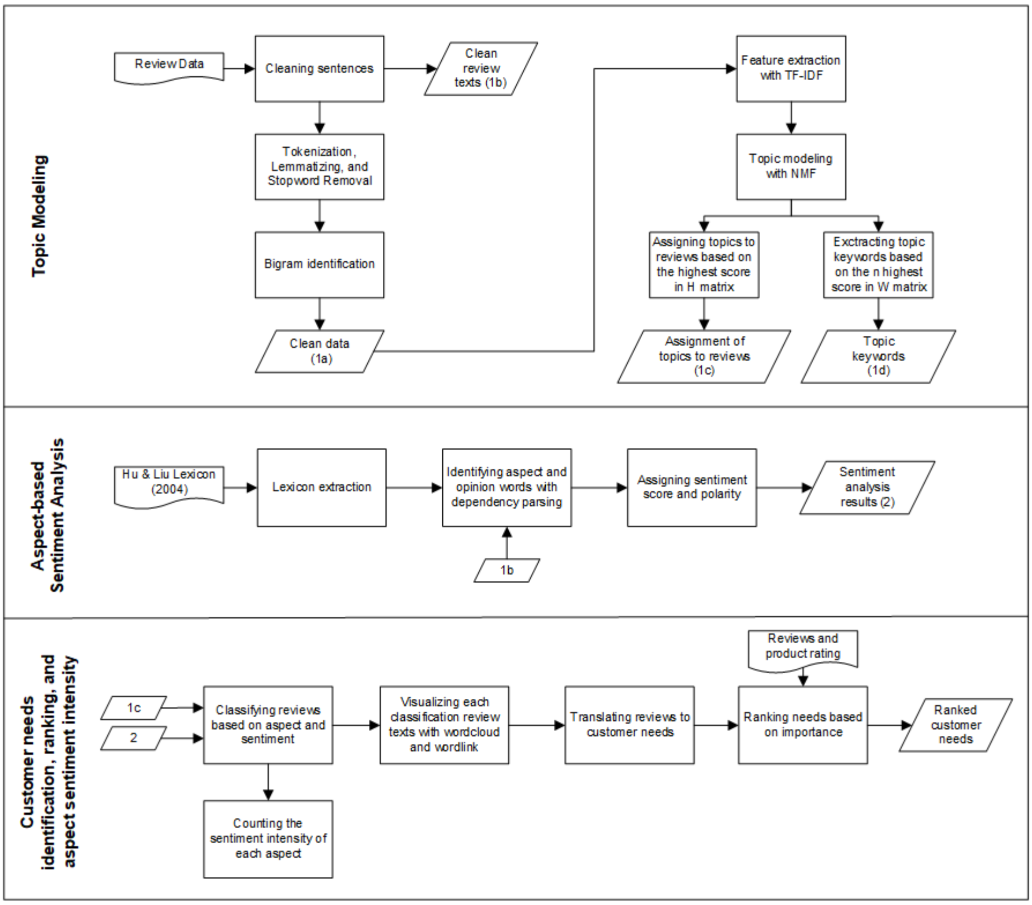


Figure 2. Proposed Methodology

Each review in this classification is visualized using word cloud and word link. It aims to see the most frequently mentioned words in these reviews and set them as keywords. These keywords are then manually searched for back in the reviews and interpreted into consumer opinions. All customer opinions are then translated into customer needs. The referred guidelines in expressing the customer opinions to customer needs are [7]:

- Express the need in terms of what the product has to do, not in how it might do
- Express the need as specifically as the raw data
- Use positive phrasing
- Express the need as an attribute of the product
- Avoid choosing the words must and should.

D. Aspect Sentiment Intensity

The sentiment intensity of aspect is obtained by calculating the overall sentiment score which is the selected sentiment based on the number of reviews. The score calculation is done with the Equation 6.

$$I_x = \frac{\sum_n^(i = 1) s_1, ..., s_n}{N} \tag{6}$$

Where I_x represents the intensity of aspect x, s_n represents the score for the n-th review in the sentiment classification, and N represents the total number of reviews of the aspects.

E. Needs Ranking Based on Importance

Needs will be ranked based on importance. The importance score is calculated based on the frequency and the comparison between the rating when a need arises and the average rating. The score calculation is done with Equation 7.

$$S_x = f_x \times ABS(OR - AR) \tag{7}$$

Where S_x represents the score of need x, f_x represents the frequency of need x, OR represents the product's overall rating, and AR is the average rating of need x.

4. Results

The data consist of 534 data reviews of ASUS Vivobook 15 F512DA and 1.902 data reviews of several other laptops that were quite similar. The amount of data gathered is 2.353 data reviews, with 83 reviews not in English being reduced from the data. The process begins with preprocessing text, and the amount of data was increased to 11.413 data reviews after preprocessing. The example of preprocessing can be seen in Table II.

Algorithm 1: Aspect Extraction Algorithm

```
input  : Opinion lexicon and sentences
output: Aspect and Opinion
A ← token-head;
a ← token;
B ← token-child;
b ← token sub-children;
for a ∈ sentence do
    if a ∈ opinion words then
        if a dependency = "advmod" then continue;
        else if a dependency = "amod" then
         Append terms(a,A);;
        else
            for B ∈ token children; do
                if a POS tag = "VERB" & B
                 dependency = "dobj then
                    Append terms(a,B);
                end
                for b in token-child children do
                    subchildren = [] conj = 0 if b =
                     "and" then
                        conj = 1 if conj = 1 & b ≠
                         "and" then  conj = 0
                        Append subchildren(b);
                    end
                    for b in token-child children do
                        Append terms(a,b)
                    end
                end
            end
            for B ∈ token children; do
                if a POS tag = "NOUN" & B not yet
                 detected then
                    n
                end
                oun = B for b in token-child children
                 do
                    if b dependency = "compound"
                     then
                        n
                    end
                    oun = b + noun Append
                     terms(a,noun)
                end
            end
            for B ∈ token-head children; do
                if B POS tag = "NOUN" & B not
                 yet detected then
                    noun = B
                end
                for b in token-child children do
                    if b dependency = "compound"
                     then
                        n
                    end
                    oun = b + noun Append
                     terms(a,noun)
                end
            end
        end
    end
end
```

TABLE II. Preprocessing Results

Review	Sentences Tokenization	Case folding, punctuation & number removal	Lemmatization, stopwords removal, & bi-gram
Beautiful look for the laptop, great hard drive space and SSD is killer. Great for traveling whether it be work or class and easy to use.	Beautiful look for the laptop, great hard drive space and SSD is killer	beautiful look for the laptop great hard drive space and ssd is killer	['beautiful', 'look', 'laptop', 'great', 'hard', 'drive', 'space', 'killer']
	Great for traveling whether it be work or class and easy to use	great for traveling whether it be work or class and easy to use	['great', 'travel', 'work', 'class', 'easy']
Does what it needs to do for the most part. Mainly surfing the web and online courses..two cons I'm disappointed about is the battery life and the flimsy keyboard.	Does what it needs to do for the most part	does what it needs to do for the most part	['useless', 'paper-weight', 'need']
	Mainly surfing the web and online courses	mainly surfing the web and online courses	['mainly', 'surf', 'online', 'course']
	two cons I'm disappointed about is the battery life and the flimsy keyboard	two cons im disappointed about is the battery life and the flimsy keyboard	['con', 'disappoint', 'battery_life', 'flimsy', 'keyboard']
Has a genaric feel to it..	Has a genaric feel to it	has a genaric feel to it	['genaric', 'feel']

After the preprocessing text, feature extraction is done with TF-IDF method. The feature extraction results showed 1,598 words identified with a certain TF-IDF value. Every word and value is stored in a matrix called the document-term matrix and document-term matrix then becomes the input for the topic modeling process. The number of topics determined in this study was 10. The keywords on each topic are the 20 words with the largest approximate value in the matrix W, as shown in Table III. The result of topic modeling shows 10 topics that can be interpreted as laptop aspects, i.e., general, battery, storage, screen, price, performance, keyboard, warranty issue, others, and design as presented in Table IV.

TABLE III. W Matrix

Topic	Words				
	ability	able	absolute	...	zero
0	0.00411	0.00866	0.00777	...	0.00345
1	0.00207	0.00987	0.00096	...	0.00000
2	0.00149	0.01818	0.00000	...	0.00000
3	0.00179	0.00938	0.00118	...	0.00000
4	0.00000	0.00956	0.00539	...	0.00000
5	0.00326	0.01319	0.00000	...	0.00000
6	0.00406	0.00798	0.01429	...	0.00075
7	0.00000	0.00594	0.00000	...	0.00000
8	0.00107	0.11253	0.00191	...	0.01817
9	0.00402	0.00144	0.00018	...	0.00624

TABLE IV. Topic Keywords

Topic	Keywords
Topic 0 (General)	laptop, overall, purchase, school, gaming, upgrade, week, replace, want, budget, absolutely, cheap, money, receive, performance, make, sound, speaker, bad, pretty
Topic 1 (Battery)	battery_life, battery, life, hour, charge, pretty, light_weight, decent, long, last, advertise, charger, average, performance, size, usage, mode, weight, plug, depend
Topic 2 (Storage)	hard_drive, drive, hard, slow, replace, solid_state, upgrade, come, sata, state, speed, solid, boot, storage, space, clone, mechanical, disk, model, install
Topic 3 (Screen)	screen, quality, black, bright, turn, touch, color, touch_screen, go_black, come, angle, display, brightness, die, blank, size, stop, view_angle, resolution, flicker
Topic 4 (Price)	price, price_point, quality, price_range, overall, spec, build_quality, performance, point, especially, find, range, worth, decent, pretty, machine, value, beat, Definitely, upgrade
Topic 5 (Performance)	fast, boot, lightweight, super_fast, pretty, easy, start, charge, speed, wifi, processor, load, extremely, beautiful, storage, second, quiet, thing, machine, battery
Topic 6 (Keyboard)	keyboard, backlit_keyboard, backlit, feel, type, key, power_button, keyboard_backlit, flex, button, thing, cap_lock, get, backlight, keyboard_flex, decent, mouse, complaint, power, cheap
Topic 7 (Warranty Issue)	month, purchase, stop, die, fail, problem, couple_month, warranty, turn, couple, display, start, backlight, later, repair, black, barely, month_later, battery, send
Topic 8 (Others)	time, issue, slow, return, update, boot, window, thing, machine, problem, take, purchase, review, start, turn, try, send, second, come, hour
Topic 9 (Design)	look, light, light_weight, feel, thin, Gaming, thin_light, weight, display, game, School, pretty, want, small, Portable, easy, cheap, powerful, sleek, come

Table V shows the value in the H matrix. The next step was to find the sentiment of each review; the results are shown in Table VI. The process conducted using a lexicon-based method with the lexicon used is the opinion lexicon by Hu and Liu [21]. The reviews data used is only 2.176 data reviews of the ASUS Vivobook 15 F512DA laptop. All reviews are then classified based on the aspects and the sentiment. The result of the classification is available in Figure 3. Sentiment for the overall aspect is determined based on the highest number of reviews in the sentiment classification.

TABLE V. H Matrix

Document	Topic				
	0	1	2	...	9
0	0.03	0.00	0.00	...	0.00
1	0.00	0.00	0.00	...	0.00
2	0.00	0.00	0.00	...	0.00
3	0.00	0.00	0.19	...	0.19
...	...	...	...	...	...
11413	0.02	0.00	0.00	...	0.01

TABLE VI. Aspect-Based Sentiment Analysis Results

Positive Reviews	
Review	beautiful look for the laptop great hard drive space and ssd is killer
Topics	['General', 'Storage', 'Design']
Dominant topic	Storage
Aspect & Opinion Word	beautiful look, great space
Score	2
Polarity	Positive
Negative Reviews	
Review	two cons im disappointed about is the battery life and the flimsy keyboard
Topics	['Battery', 'Keyboard']
Dominant topic	Battery
Aspect & Opinion Word	flimsy keyboard
Score	-1
Polarity	Negative

Customer needs identification begins with visualizing reviews in every classification using word cloud and word link. Like the two reviews shown in Table VI, the positive review included the storage aspect. The aspect keywords are hard drive, SSD, drive, plus, and storage with the opinion words great, fast, killer, like, and huge, as illustrated in Figure 4. This review then translated where the customer thinks the laptop hard drive and SSD space are spacious.

In the negative review, the dominant topic was the battery, even though the identified aspect and opinion were a flimsy keyboard. The aspect keywords in battery topic with negative sentiment are computer, life, battery, and gaming with opinion words dead, kills, dies, and flimsy as illustrated in Figure 5. The negative review then translated where the customer argues that the laptop battery life is not in line with customer expectations. Overall, 30 customer needs that are identified of in all aspects, as shown in Table VII.

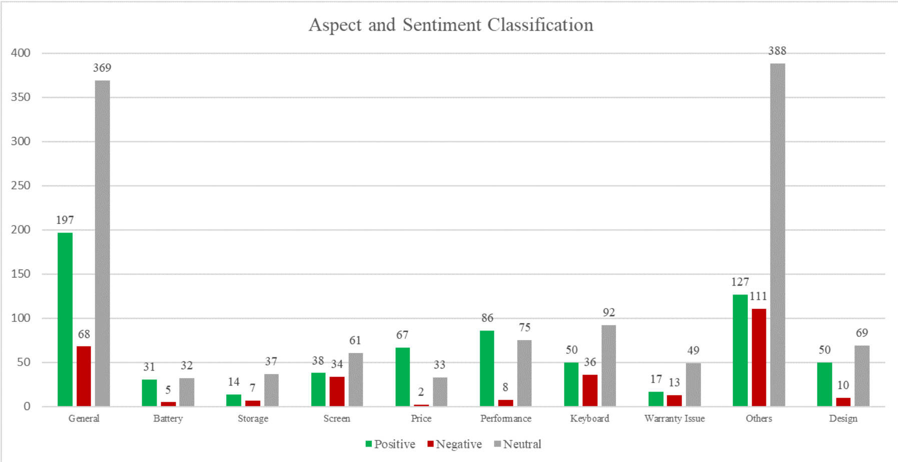
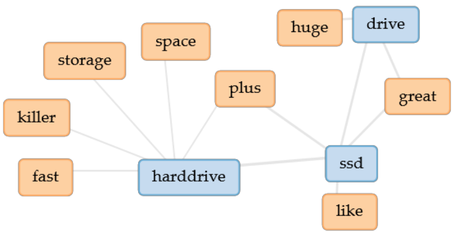


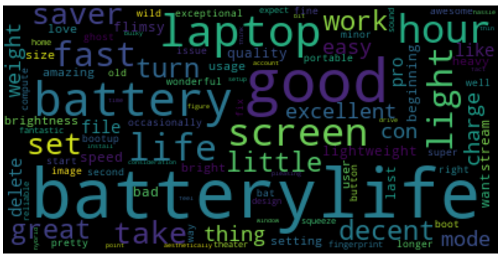
Figure 3. Aspect and Sentiment Classification

(a) Worcloud

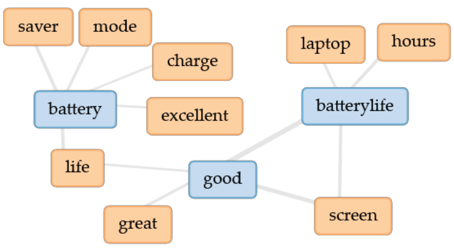


(b) Wordlink

Figure 4. Storage-Positive Keywords Visualization



(a) Worcloud



(b) Wordlink

Figure 5. Battery-Negative Keywords Visualization

TABLE VII. Aspect-based Customer Needs

Topic	Needs
General	Well-functioning audio, ideal speaker position, a good quality laptop
Battery	battery with a minimum endurance of 8 hours, a battery that works well, and a good type of charger port
Storage	Large SSD and hard drive capacity, SSD capacity of more than 128 GB, fast storage speed, and a dual-storage system
Screen	screen with a good IPS system, bright screen colors, sharp screen resolution (clear), good screen strength, and a thin bezel
Price	Competitive prices, the price set according to quality, affordable prices
Performance	Fast and responsive processor, fast and responsive fingerprint scanner
Keyboard	Keyboard with a backlit feature, ergonomic keyboard design, responsive keyboard keys, power button located outside the keyboard, and keyboard material with a luxurious feel
Others	Good quality of screen graphics, large memory, well-functioning charger
Design	Slim laptop design, light laptop weight, compact charger design

Each need then will be ranked based on the importance score. The frequency is measured by searching the related keyword based on NMF results using panda, regex, and Numpy packages, and the overall rating is 4.2. The importance score and the rank of each need are in Table VIII. The result shows that a laptop with a good screen strength has the highest score of all, which means that the durability of the screen is the most significant aspect for the customer, with a fast and responsive processor as the second most important.

TABLE VIII. Customer Needs Rank

Rank	Needs	Freq.	Avg. Rating	S_x
1	Good screen strength	21	1.67	53.20
2	Fast and responsive processor	96	4.45	23.80
3	Responsive keyboard keys	23	3.22	22.60
4	Fast storage speed	35	3.66	19.00
5	Keyboard material with a luxurious feel	16	3.50	11.20
6	Price set according to quality	20	3.80	8.00
7	Competitive prices	58	4.09	6.60
8	Power button located outside the keyboard	12	3.67	6.40
9	Light laptop weight	42	4.07	5.40
10	Battery with a minimum endurance of 8 hours	16	3.88	5.20
11	Slim laptop design	13	3.85	4.60
12	A good quality laptop	9	4.56	3.20
13	Good quality of screen graphics	1	1.00	3.20
14	A battery that works well	35	4.29	3.00
15	Large memory	6	4.67	2.80
16	Ergonomic keyboard design	2	3.00	2.40
17	Well-functioning charger	2	3.00	2.40
18	Compact charger design	2	3.00	2.40
19	SSD capacity of more than 128 GB	3	3.33	2.60
20	Fast and responsive fingerprint scanner	5	4.60	2.00
21	A well-functioning audio	4	3.75	1.80
22	A good type of charger port	2	5.00	1.60
23	Dual storage system	3	3.67	1.60
24	Screen with a good IPS system	3	3.67	1.60
25	Affordable prices	8	4.00	1.60
26	Large SSD and hard drive capacity	5	4.00	1.00
27	Bright screen colors	5	4.00	1.00
28	Ideal speaker position	1	5.00	0.80
29	A thin bezel	2	4.50	0.60
30	Keyboard with backlit feature	8	4.13	0.60
31	Sharp screen resolution (clear)	2	4.00	0.40

Based on the number of reviews from each aspect-sentiment classification, the polarity of every aspect concluded as positive. The intensity of the sentiment is conducted by calculating the total score and dividing it by the total number of reviews in each classification. The higher the intensity of the sentiment, the more positive the polarity. Positive polarity shows that consumers feel that aspects of the product have met or exceeded their expectations. As shown in Table IX, the price has the highest intensity; it can be concluded that the products have exceeded customer expectations on the price aspect.

TABLE IX. Sentiment Intensity Calculation Results

Aspect	Polarity	Sentiment Intensity
Battery	Positive	0,838
Storage	Positive	0,276
Screen	Positive	0,489
Price	Positive	1,054
Performance	Positive	0,928
Keyboard	Positive	0,430
Warranty Issue	Positive	0,259
Others	Positive	0,263
Design	Positive	0,655

5. Discussion

The program design shows that the results of topic modeling are relatively good. In this study, the LDA method was used to conduct topic modeling. However, LDA's highest coherence score only reaches 0.3571 with five topics, and it is hard to interpret, as shown in Table X and Figure 6. The NMF method provides topics that are easier to interpret. Since the reviews were tokenized into sentences, a review became a short text collection. As previously mentioned, NMF tends to have better performance than LDA in processing short texts [38]. Several topics are not easily comprehended, such as the topics of warranty issues and others. Both topic's keywords cannot be interpreted as certain aspects of the laptop, as shown in Table IV. In addition, the assignment of topics with the highest approximate value may cause some not to be identified during sentiment analysis.

TABLE X. LDA Topic Keywords

Topic	Keywords
Topic 0	fast, light, laptop, purchase, issue, slow, screen, display, look, fine, thin, keyboard, battery, machine, lightweight, boot, speed, price, drive, return
Topic 1	laptop, sound, drive, thing, screen, time, issue, turn, want, battery, fast, speed, power, start, solid, video, keyboard, lightweight, light, boot
Topic 2	laptop, month, look, battery, fast, screen, life, charge, last, time, hour, quality, easy, hope, speed, speed, value, high, price, feel, issue
Topic 3	laptop, fast, light, return, screen, quality, start, Microsoft, keyboard, model, enjoy, office, program, thank, gaming, backlight, miss, touch, update
Topic 4	price, laptop, screen, value, keyboard, light, month, fast, absolutely, fame, black, travel, battery, time, money, perform, cheap, fail, reliable, life

There is a limitation in topic modeling by using a dominant topic based on dividing reviews. A review may

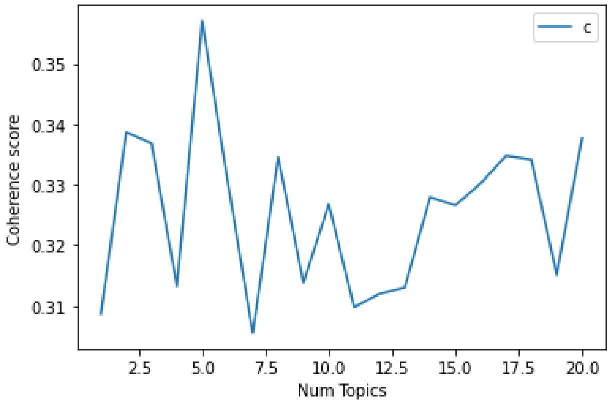


Figure 6. LDA Coherence Score

contain more than one topic, and the identified aspect sentiment may not related to the dominant topic. A better classification method that can identify every topic may be preferable, so the translation of customer needs can be more accurate.

Sentiment analysis also gave quite good results. Several words of opinion can be identified along with aspects of the opinion word, and this can be caused by lexicon selection and category determination. In previous research [24], opinion lexicon Hu and Liu [21] gave good results in the sentiment categorization of product reviews with an accuracy rate of 75-77%. The categories that have been determined have also covered quite a broad search for aspects by looking at the head, sub-words, and siblings of the opinion word. However, sentiment analysis results will be better if it can focuses on sarcasm words, opinion words with a broad meaning (adjectives or verbs), and substitute words.

The use of text mining methods cannot completely replace other methods such as interviews and focus groups in identifying customer needs. Several limitations to the using text mining methods include limited resource profiles and unexpected needs that cannot be identified. So, the results of this can only be of assistance in the process of identifying customer needs related to consumer views of the product through online data reviews, which, if processed manually, will require quite high time, effort, and cost [7].

Several needs are specific for the type of laptop with the Vivobook type, namely the location of the power button, which is outside the keyboard, and the ideal speaker position. In general, Vivobook type laptops have a power button integrated with the keyboard, and the speaker position is underneath it. These things are something that customers generally complain about in reviews because it is easy to make a mistake in pressing the power button, and the sound will be blocked when placed on a sound-absorbing mat. Although the rank of this need is not relatively high, it will be better if the company pays attention to this need. In addition, there is a need that is not common but is necessary for this laptop, namely the form of a compact charger design. Customers prefer a compact charger design due to the ease of storage and lighter load when traveling. The usual charger design is adjusted to the size of the power required. So, it would be better if the company could design a compact charger with adequate power that suits the needs of the laptop.

6. Conclusion

Identifying customer needs is an important part of product development's early stage. This paper provides a methodology to identify customer needs based on online reviews to help product designers obtain insightful customer information in their decision-making process. There are three main stages; the first stage is topic modeling. The application of topic modeling with NMF gave quite good results in defining the topics discussed by customers. The obtained result shows there are 9 topics. The second stage is aspect-based sentiment analysis. Lexicon-based approach with Hu & Liu lexicon is proposed for aspect-based sentiment analysis to identify the sentiment for each topic. It used dependency parsing to extract the opinion target.

The third stage is customer needs identification, ranking, and aspect sentiment intensity. Based on the reviews in each topic and its sentiment, keywords were found using word link and word cloud. Keywords then translated into customer needs and there were 30 customer needs identified. Each need is ranked based on the importance score and each topics' sentiment is calculated to provide product designers with greater insight into enhancing or developing products. The results show that in further product development, products designer can prioritize a product with a good screen strength, fast and responsive processor, and responsive keyboard keys. The sentiment intensity also shows that all product features have a positive polarity hence the product has met customers' expectations.

For future work, detecting implicit opinion words such as sarcasm words can be used to improve the sentiment analysis further. To give further information about customers, customer segmentation and Kano model can also be adapted to the proposed method. Customer segmentation can help product designers in identify their target audience, leading to better customer satisfaction. The improvement or development of products can affect customer satisfaction differently, thus Kano model can classify product features based on their impact on customer satisfaction.

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