Utilizing Online Reviews for Human Resource Development in the Retail Industry Using Aspect-based Sentiment Analysis

Gregorius Ferrari Pramudika*, Ririn Diar Astanti, Ignatius Luddy Indra Purnama
Departement of Industrial Engineering, Universitas Atma Jaya Yogyakarta, Indonesia

Email: 225612163@students.uajy.ac.id, ririn.astanti@uajy.ac.id, luddy.indra@uajy.ac.id

*Corresponding author

ABSTRACT

The growth in the retail industry means that the retail industry must have a competitive advantage to compete. One source of competitive advantage is customer experience. One factor that has a positive influence on customer experience is the service provided by frontline employees. Nowadays, customers can easily share their experiences and information in online reviews. Therefore, a good understanding of online reviews is necessary to maintain customer satisfaction. This paper proposes a new method for obtaining information from online reviews available on online review platforms such as Google Maps. Reviews on the website will be scraped and translated into English using the large language model (LLM). The translated reviews will be translated to obtain aspects, sentiments, and opinions using an aspect-based sentiment analysis (ABSA) model that has been previously drilled using a dataset in English. The findings are visualized into Pareto diagrams and word cloud to identify aspects related to human resources that most influence the negative or positive ratings given by customers through online reviews.

DOI: https://doi.org/10.24002/ijieem.v6i2.9092

Keywords: aspect-based sentiment analysis, human resource, large language, online review, retail industry

Research Type: Research Paper

Article History: Received May 1,2024; Revised July 6, 2024; Accepted August 13, 2024

How to cite: Pramudika, G.F., Astanti, R.D., & Purnama, I.L.I. (2024). Utilizing online reviews for human resource development in the retail industry using aspect-based sentiment analysis. *International Journal of Industrial Engineering and Engineering Management, 6*(2), 75-85.

1. INTRODUCTION

The retail industry in the world is expected to follow an increasing growth trend in the future. In 2024, retail growth is estimated to reach 4.9% and will have an impact on increasing total world retail sales to $31.1 trillion (Oberlo, 2024). With the intense competition in the retail industry sector, every retail industry must be able to increase its competitive advantage. Customer experience in shopping is the main source of competitive advantage for the retail industry. Therefore, the retail industry must always improve customer experience to maintain customer satisfaction.

Customer experience of the services provided by employees, especially frontline employees, is one of the factors that has a positive influence and is a prerequisite for customer satisfaction in retail (Pei et al., 2020). So that the performance of frontline employees in providing services to customers can always be optimal, human resource analytics (HRA) is needed to maintain employee performance. At this time, HRA can utilize internal company data or very large amounts of external data (big data) so it requires modern, capable analytical techniques (Tonidandel et al., 2018). One external data that can be utilized is online reviews from customers. With the development of the internet today, customers can easily share experiences and information in online reviews (Kim & Kim, 2022). Online reviews can also be used to see the level of customer satisfaction directly and used as input to improve the customer experience (Shin et al., 2022). A good understanding of online reviews is very necessary to maintain customer satisfaction because customers will consider online reviews as a useful source of information and can greatly influence consumer decision-making (Duan et al., 2008; Heo & Bae, 2020; Kim & Kim, 2022; Shin et al., 2022). One online platform for writing online reviews of a location is Google reviews. Google reviews provide information in the form of ratings and reviews made by users of a business about customer experience, and product quality among others. Google reviews also contribute to search engine optimization (SEO) by considering the rating level and number of reviews to determine the order of search results (Wiley, 2023). There are a very large number of online reviews on platforms such as Google reviews as the popularity of web-based review writing platforms increases. Because of those platforms, previous reviews will quickly be covered by new reviews and this means that the information in the reviews cannot be obtained easily due to the large amount of data (Lee & Yu, 2018).

Since the 1960s, there has been a branch of applied artificial intelligence (AI), namely data mining techniques. Data mining techniques, such as generalization, characterization, classification, clustering, association, evolution, pattern matching, data visualization, and meta-rule guided mining, enable the search for valuable information from large amounts of data (Liao et al., 2012; Weiss & Indurkhya, 1998). Later on, there is also an increase in the amount of unstructured data, for example, text data. Conventional data mining techniques are incapable and difficult to use to process text data. When dealing with text data, text mining techniques or text data mining are needed (Tandel et al., 2019). Text mining is a technique for exploiting the power of unstructured text data by analyzing it, generating new knowledge, and identifying hidden patterns and correlations in the data (Hassani et al., 2020). One of the techniques in text mining is sentiment analysis. Sentiment analysis is a text mining technique used to determine the contextual polarity of a piece of writing, whether the writing is expressed negatively, neutrally, or positively (Shukri et al., 2015). In its development, there is an aspect-based sentiment analysis (ABSA) technique that can be used to find aspects in a sentence and determine the sentiment of each aspect, not just inferring the polarity of the overall sentiment of a sentence (Pontiki et al., 2014).

This paper discusses the application of sentiment analysis techniques, especially ABSA, in the field of human resource analytics in the retail industry. Various studies have used ABSA to find the information contained in a review. To the best of the researcher's knowledge, there has been no research that utilizes ABSA to examine the need for human resource development, especially in the retail industry. Additionally, most studies perform ABSAs that are created specifically for a particular language (Chamid et al., 2022; Essebbar et al., 2021; Yanuar & Shiramatsu, 2020). ABSA created specifically for a particular language has the potential to have shortcomings, namely that it is not flexible when used to analyze sentences in other languages. Therefore, this paper attempts to fill the gap in terms of the application of ABSA to identify aspects, sentiments, and opinions as a basis for human resource development in the retail industry based on online reviews and create a more flexible ABSA framework to accept input from various languages.

2. LITERATURE REVIEW

2.1. Service quality in the retail industry

Customer satisfaction in the retail industry is greatly influenced by service quality through various factors (Wu et al., 2020; Ying et al., 2021). Based on the customer's view, employees at a retailer represent the company where they work. Employees are also responsible for creating value to provide quality service for customers (Judd, 2003; Pei et al., 2020). Service quality focuses on how customers can achieve their expectations which ultimately can influence their intention to purchase (Papademetriou et al., 2023). Service is an activity that is intangible and usually occurs, but not necessarily, in interactions between customers and service employees (Grönroos, 1990). To produce good service quality, the role and intervention of human resource development are very important by providing added value elements such as advice, managerial skills, and training (Galperin & Lituchy, 2014). Customer-centric business models are becoming important in the retail industry. So, increasing frontline employee involvement and customer-oriented behavior is one of the main factors influencing business performance in the service industry (Ghlichlee & Bayat, 2021).

2.2. Leveraging human resource analytics for enhanced human resource development

Human resource analytics (HRA) is a process for collecting, analyzing, interpreting, and reporting human-related data to improve decision-making, achieve strategic goals, and maintain competitive advantage (Bauer et al., 2023). Based on Caughlin (2024), in building an HRA several phases must be passed which are summarized in the HRA project life cycle (HRAPLC). HRAPLC consists of question formulation, data acquisition, data management, data analysis, data interpretation, and storytelling, as well as deployment and implementation. The use of the project life cycle framework in HRA aims to ensure that human resource analysis can be developed effectively.

Bonilla-Chaves & Palos-Sánchez (2023) have explored the development of HRA and stated that currently, the main topics related to HRA are related to the use of big data, artificial intelligence, and machine learning in HRA. Data and analytical tools are used to make decisions based on information regarding employee management and organizational performance. One example that utilizes the use of modern analytical techniques such as big data is carried out by Raguvir & Babu (2020) which researches to understand and improve human resources by identifying important factors that influence employee performance and supporting management decisions through people analytics by collecting data from multinational HR companies and using visual analytics, namely Kibana and Elasticsearch. Besides that, Alsaadi et al. (2022) also developed an HRA method based on machine learning algorithms to identify critical elements that influence employee resignation at the company. The research used techniques such as decision trees, logistic regression, random forest, and K-means clustering to predict the probability of new employees' resignations and found that employee resignation was significantly influenced by overtime, total projects, and job level.

In HRA, two types of data sources can be utilized, namely internal and external data. Internal data is data in the form of human resource metrics, such as absenteeism rates, success in recruiting new employees, training costs, and so on. Meanwhile, external data is data that is very easy to obtain outside of the company's internal data (Pijpers et al., 2023). This research proposes the use of external data, namely online reviews, as a basis for conducting human resource analytics to support human resource development. Online reviews provided by customers are one part of a series of purchases made by many customers. Currently, online reviews can be found on various websites, such as Yelp, Facebook, Google, IMDb, and many more (Askalidis & Malthouse, 2016). Reviews given by customers can be used as a source for obtaining various information (Trenz & Berger, 2013). Online reviews have two important aspects to a business, namely online reviews can influence future customers through electronic word-of-mouth and can help businesses understand their customers (Xu, 2021). One of the uses of online reviews for certain purposes is carried out by Zhao et al. (2019) which explains that customer online reviews have a very important value in business and can be used to predict overall customer satisfaction. Li et al. (2023) also utilize online reviews containing customer needs and expectations as a basis for identifying product design opportunities. Apart from that, there is also the use of online reviews related to human resources carried out by Xu (2021) who studied online reviews made by customers of restaurants on on-demand service platforms using text mining and text regression techniques. With so much information that can be obtained from online reviews provided by customers, it challenges researchers to explore the use of online reviews to improve the business process including in the retail sector. This motivates the research presented in this paper. The research presented in this paper utilizes online reviews as a basis for conducting human resource analytics to find customer criticism of the retail shopping experience as a basis for human resource development. The use of external data, such as online reviews, to analyze human resources can also be used to complete analysis using internal data as is often done.

2.3. Sentiment analysis and aspect-based sentiment analysis

Sentiment analysis is an activity to obtain and analyze a person's opinions, sentiments, attitudes, or perceptions of entities such as topics, products, and services. Sentiment analysis is a powerful tool for obtaining and analyzing people's views, gaining business insights, and making better decisions based on opinions and reviews posted by people on internet-based applications, websites, social networks, and blogs (Birjali et al., 2021). The use of sentiment analysis to obtain information from text data has been widely used in various fields, for example in product development activities (Ireland & Liu, 2018; Sutrilastyo & Astanti, 2021), measuring sentiment on social media during Covid-19 (Hota et al., 2021), Legitimacy analysis of wind-powered power plants from articles published in newspapers (Dehler-Holland et al., 2022), and other specific uses.

Aguilar-Moreno et al. (2024) analyze the use of sentiment analysis techniques to support business decision-making. Based on the results of this analysis, sentiment analysis is often carried out on data taken from social media and online reviews by conducting opinion mining. Sentiment analysis is often carried out in various areas of industry, such as supply chains and risks, customer views of companies, and after-sales services, as well as in the financial banking, stock market, and cryptocurrency sectors.

In its development, sentiment analysis was categorized into three levels, namely at the document level, sentence level, and aspect level. Sentiment analysis at the aspect level or aspect-based sentiment analysis (ABSA) is the most detailed level of sentiment analysis because it can enable opinion predictions at the aspect level (Cambria et al., 2017). There have been various studies that utilize ABSA to analyze text data for various purposes, for example, to identify aspects and sentiments from tourism reviews using convolutional neural networks (CNN) (Nayoan et al., 2021), to create a restaurant information dashboard in Indonesia based on online restaurant review data using semi-supervised ABSA (Tedjojuwono & Neonardi, 2021), and to utilize online reviews as a decision support system using bidirectional encoder representations from transformers (BERT) (Yanuar & Shiramatsu, 2020).

Based on the review carried out, the use of sentiment analysis techniques mostly focuses on the marketing area to identify customer perceptions of the company or product as well as on the operations area to identify risks (Aguilar-Moreno et al., 2024). To the best of researchers' knowledge, there are still not many applications of sentiment analysis in the human resource area. This research proposes the use of sentiment analysis, especially ABSA, to analyze online reviews as a basis for human resource development.

2.4. Large language model for language translation

Large language models (LLM) currently have capabilities in various types of tasks and show capabilities that approach or even exceed human intelligence. Of the various tasks that can be carried out, the translation carried out by LLM shows satisfactory results (Agrawal et al., 2023; He et al., 2024; Jiao et al., 2023). With research on artificial intelligence (AI), generative AI has been produced which can create new things after learning from trained models. Companies such as Google Brain, Facebook, and OpenAI have developed various generative AI models built on LLM (Barreto et al., 2023). Siu (2023) researched one of the generative AI, ChatGPT, to carry out tasks as a translator. ChatGPT has the potential to revolutionize the language industry due to its capabilities as a powerful language model based on the Transformer architecture. However, when using

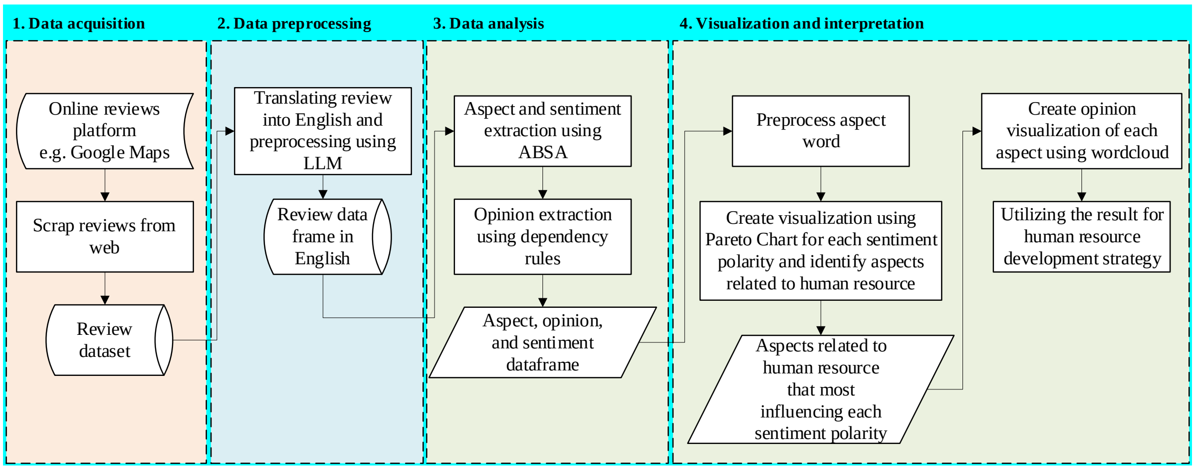


Figure 1. Proposed method for analyzing online reviews

generative AI that has been provided by a company and can only be accessed via the Application Programming Interface (API), security and stability issues need to be considered. All prompts and input text must be uploaded to the server to be processed and get results, so this method is considered less suitable for translating sensitive information. System stability can also be a consideration because with more users, the server will require high computing capabilities and there is a possibility of downtime and delayed responses.

3. METHOD

Figure 1 is a proposed method for identifying human resource development needs based on data from online reviews using ABSA.

3.1. Data acquisition

Online review data is obtained by scraping from online review platforms, for example, reviews on Google Maps. To meet these needs, the data collection process was carried out using the Selenium WebDriver to automate the web browser (Selenium Community, 2021). An example of web browser automation that can be done is scrolling on a website so that the website can load more online reviews. Selenium WebDriver can be used in the Python programming language with the Selenium library (Muthukadan, 2024) or R language with the RSelenium library (Harrison, 2022). After the online reviews are loaded on the website, the next step is to scrape the online reviews. Scraping can be done using the BeautifulSoup library (Richardson, 2023) in the Python programming language or R language by using the rvest library (Wickham, 2024).

3.2. Data preprocessing

The online review data obtained from the previous stage may be written in more than one language. So, the review data that has been collected will be translated into English before being analyzed further. The translation process is carried out by utilizing the LLM developed by Google, namely Gemini. The translation process is carried out by giving a prompt to Gemini to translate the given text. The text input provided is formatted in JSON form and the output produced by Gemini is also in JSON format. The JSON format was chosen to facilitate the subsequent analysis process using Pandas Dataframe. Before carrying out the translation process, the review data is cleaned first to reduce failures when saving the Gemini output JSON. The Gemini model used for the process of translating review data is "gemini-1.0-pro-latest". The prompt given to Gemini was as follows:

You are an expert linguist, who is good at translating sentences from Indonesian to English.
Help me translate sentences provided between three backticks.
Please translate with good grammar.
Please do not translate word by word.
In your output, only return the JSON code as output - which is provided between three backticks.
If there is a quotation mark or anything symbol that may cause an error in the JSON code in a sentence, please remove it from the output JSON.
Your task is to update translate labels under 'translate' in the JSON code.
Error handling instruction: In case a sentence violates API policy, please assign it as a translation Error.
Don't make any changes to the JSON code format, please.

```
{json_data}
```

Because the review data input sometimes has a writing structure that does not follow the grammar of the original language, the resulting translation also has the possibility of not following English grammar. To overcome this, preprocessing of the translation results was also carried out to make it more in line with English grammar. Sentences with poor grammar can cause inappropriate analysis results. Grammar improvements are also carried out using the LLM, Gemini. Similar to the previous stage, input and output data at this stage are also provided in JSON format to make it easier to modify the data at the next stage. The prompt given to Gemini was as follows:

~~~
You are an expert linguist, who is good at checking and repairing the grammar in a text.
Help me to repair sentences provided between three backticks.
Please repair with good grammar, do not use a contraction.
In your output, only return the JSON code as output - which is provided between three backticks.
If there is a quotation mark or anything symbol that may cause an error in the JSON code in a sentence, please remove it from the output JSON.
Your task is to update good_translate labels under 'good_translate' in the JSON code.
Error handling instruction: In case a sentence violates API policy, please assign it to the original text.
Don't make any changes to the JSON code format, please.

```
{json_data}
```
~~~

3.3. Data analysis

3.3.1. Aspect and sentiment extraction

After all the review data has been translated and preprocessed, the data is ready for more in-depth analysis. ABSA is carried out to extract aspects and sentiments contained in each review. ABSA is performed using a pre-trained model provided by the pyABSA library. pyABSA facilitates the use of the ABSA technique which is based on the Bidirectional Encoder Representations from Transformers (BERT) model using the Python programming language (Yang et al., 2023). The ABSA process using pyABSA in this case study is carried out using a pre-trained model with the name checkpoint, namely "multilingual2". Because it requires quite high computing capabilities, the analysis process using pyABSA is better carried out using a Graphic Processing Unit (GPU).

3.3.2. Opinion extraction

The next analysis is to extract opinions from each aspect found through ABSA. The process of searching for opinions for each aspect is carried out using dependency rules which are carried out using the spaCy library (Joshi et al., 2019). In these rules, there are two terms used, namely M (sentiment modifier) and A (aspect). Dependency rules use the dependency identifier contained in Universal Dependencies (2024). There are 5 dependency rules used:

a. M is a child of A with an amod (adjective modifier) relationship.
b. A is a child of a sentence with an nsubj (nominal subject) relationship and M is a child of sentence with a dobj (direct object relantionship).
c. A is a child of a sentence with an nsubj (nominal subject) relationship and M is a child of a sentence with an acomp (adjetival complement) relationship.
d. d. A is a child of a sentence with a nsubjpass (passive nominal subject) relationship and M is a child of a sentence with an advmod (adverbial modifier) relationship.
e. e. A is a child of a sentence with a nsubj (nominal subject) relationship and M is a child of a sentence with a cop (copula) relationship.

This analysis will produce pairs of aspects and opinions. So the final result is obtained by matching aspects of ABSA with aspects of dependency analysis.

3.4. Visualization and interpretation

The results of the analysis in the form of aspects and sentiments are visualized in the form of a Pareto diagram. The use of Pareto diagram was chosen because it can be used to identify critical factors with the 80/20 rule (Sanders, 1987). Meanwhile, the results of opinion analysis for each aspect will be displayed using Word Cloud. Wordcloud is a powerful text data visualization technique. The size of words in a word cloud depends on the frequency of appearance in the text. Words that appear frequently are considered more important in a text (Wang, 2022).

4. CASE STUDY

To test the proposed method, a case study was carried out to analyze customer reviews of a retailer. The case study was conducted at a retail network in the Special Region of Yogyakarta, Indonesia. All programming steps carried out can be accessed on GitHub: https://github.com/gregoriosferrari/2024-4-28_HR-Analytic

4.1. Collecting online review data

Data on customer reviews of a retailer is collected from online platforms that provide review facilities. In this case study, the data source used is reviews on Google Maps. Review data on Google Maps, shown in Figure 2, was obtained by scraping. Because the Google Maps website is dynamic, meaning more review data will be loaded when scrolling on the web page, the scrap process requires automation in the web browser.

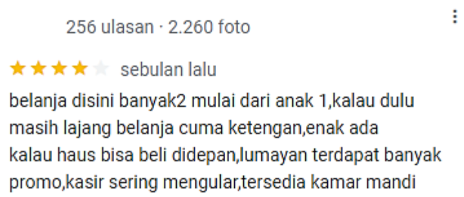


Figure 2. Review section in Google Maps

4.2. Preprocessing online review data

Online review data that has been previously collected will be translated into English before further processing. The translation process is carried out using LLM Gemini by providing the prompts described in the previous section. The resulting translation will be reprocessed to improve the grammar. In the process of translating and correcting grammar, sometimes some reviews fail to be translated or have their grammar corrected. These cases can be resolved by repeating unsuccessful processes or in this case study they will be deleted and not included in the next analysis. Figure 3 shows an example of review data that has been translated and grammatically corrected using LLM Gemini. Using this step, review data that was originally in Indonesian will be translated into English.

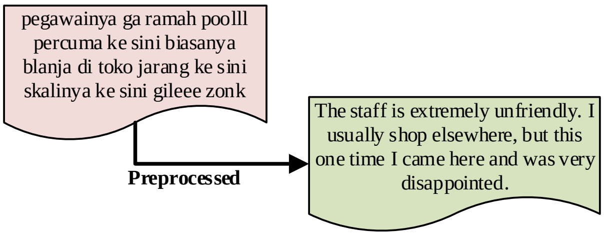


Figure 3. Example of the preprocessing stage

4.3. Analyze review data

4.3.1. Aspect and sentiment extraction

After the data collection and preparation process has been carried out, the next stage is the review data processing process to find out what causes customers to give low ratings to a retailer, especially those caused by the service provided by employees to customers. The analysis was carried out on cloud computing from Google Colab with the Linux operating system and Tesla T4 GPU. The review data analysis step begins by initializing the AspectExtractor object from the pyABSA library. Next, the review data will predict sentiment in batches. Analysis in batch form is carried out to save analysis time. The batch size is adjusted so that it is not too large or too small to avoid lost analysis results when a program failure occurs. The time required to carry out sentiment analysis from 2375 data using the computing specifications previously explained is 712.82s. The results of aspect-based sentiment analysis using the pyABSA library can be seen in Table 1.

In Table 1, there are several columns resulting from the analysis. The “sentence” column shows the review data to be analyzed, the “IOB” column shows the Inside-Outside-Beginning (IOB) tag from NLP to mark consecutive groups of words in a sentence, the “tokens” column shows the results of tokenization in the review sentence, the “sentence” column aspect" shows the aspect of discussion contained in the review sentence, the "position" column shows the index of each aspect in the review sentence, the "sentiment" column shows the sentiment classification results of each aspect found, the "probs" column shows the probability of sentiment for each aspect found, and the “confidence” column shows the level of confidence in the final sentiment classification results for each aspect.

4.3.2. Opinion extraction

The second analysis process is opinion extraction. This analysis aims to find out the reasons why an aspect is categorized as negative or positive sentiment. The results of opinion extraction can be seen in Table 2. There is a list containing ["aspects from ABSA", "aspects from dependency rules", "opinion"].

4.4. Visualization and interpretation

The results of the analysis on the previous hold are then visualized to make it easier to interpret the results. The first visualization is a Pareto diagram to find out the aspects that most influence the assessment (high or low) given by customers to a retailer. Figure 4 is a Pareto diagram formed from the ABSA results in the previous stage.

Based on Figure 3a, it is shown that most of the aspects that are most influential in generating negative assessments in reviews given by customers are dominated by aspects related to human resources. These aspects are "Cashier section", "Sales staff", "Parking attendant", and "Security staff". Meanwhile, another aspect that is also most influential in generating negative assessments from customers is aspects related to the environment or facilities in retail, namely "Parking area". In contrast to aspects that produce negative assessments, aspects that

Table 1. Aspect-based sentiment analysis result

Sentence	IOB	Tokens	Aspect	Position	Sentiment	Probs	Confidence
During Ramadan and Eid, the services should h...	[O, O, O, O, O, O, B-ASP, O, O, O, O, O]	[During, Ramadan, and, Eid, ,, the, services, ...	[services]	[[6]]	[Negative]	[[0.8696841597557068, 0.11195211857557297, 0.0...	[0.8697]

Table 2. Result from opinion extraction

Sentence	Pairs dependency_rule
During Ramadan and Eid , the services should have been faster …	[['services', 'services', 'faster'], ['services', 'services', 'faster'], ['cashier', 'cashier', 'closed']]

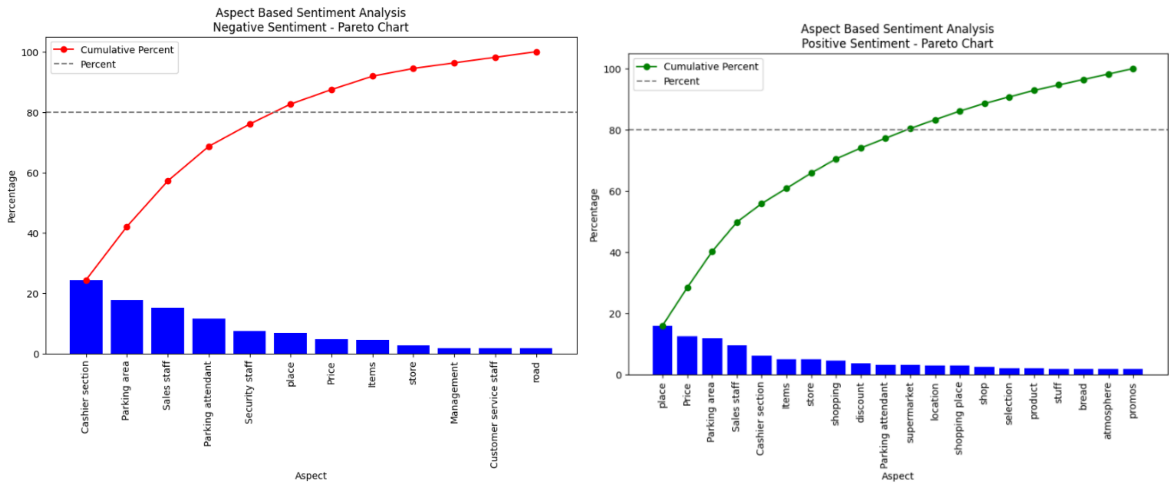
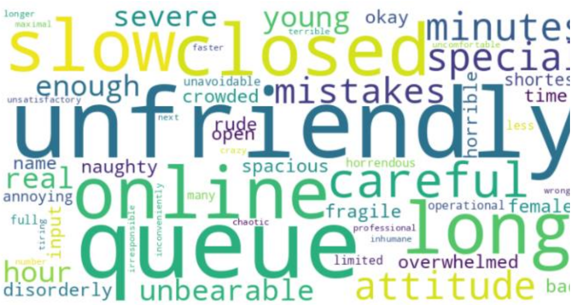


Figure 4. Pareto chart of aspects causing (a) negative sentiment and (b) positive sentiment from customer review



(a) Cashier section

(b) Sales staff

(c) Parking attendant

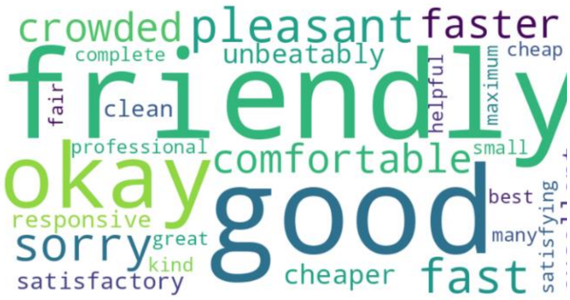
(d) Security staff

Figure 5. Wordcloud of opinion for each aspect having negative sentiment related to human resource

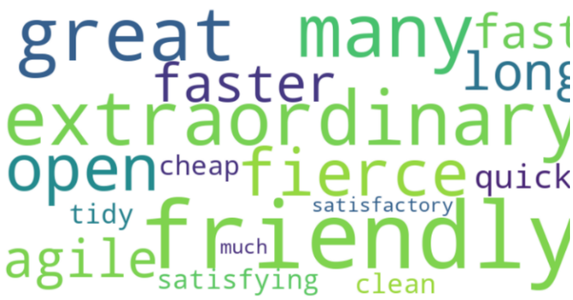
produce positive assessments (Figure 3b) from reviews given by customers are dominated by aspects related to the environment or facilities and products sold in retail, such as "Place", "Price", "Parking area ", “Items”, “Store”, “Shopping”, and “Discount”. Aspects related to human resources, such as "Cashier section", "Sales staff", and "Parking attendant", have a smaller proportion than other aspects.

By carrying out analysis to extract opinions, the cause of an aspect being classified into positive or negative sentiment can be known. Figure 5 is a visualization of opinions on every aspect related to human resources that is most influential in generating negative assessments from customers in the form of a word cloud. The "Cashier section" aspect (Figure 4a) received a negative assessment from customers due to the cashier's unfriendly and unpleasant attitude towards customers and long payment queues due to slow cashier service and closed cashiers. The "Sales staff" aspect (Figure 4b) received a negative assessment because the employee's attitude was less friendly towards customers, they were considered less competent in their work, and their service seemed slow. The "Parking attendant" aspect (Figure 4c) received a negative assessment because the attitude was less friendly and rude towards customers and was considered less helpful in the vehicle parking process. The "Security staff" aspect (Figure 4d) received a negative assessment because the attitude was less friendly and less responsive.

Figure 6 is a visualization of opinions for each aspect related to human resources that has the most influence on positive assessments from customers. The "Sales staff" aspect (Figure 6a) received a positive assessment because of their friendly, pleasant attitude and responsive or fast service. The “Cashier section” aspect (Figure 6b) received a positive assessment because of the friendly attitude and good service. The "Parking attendant" aspect (Figure 6c)



(a) Sales staff



(b) Cashier section

(c) Parking attendant

Figure 6. Wordcloud of opinion for each aspect having positive sentiment related to human resource

received a positive assessment because the service was good, friendly, and honest. However, there are also opinion results that do not match the aspects or sentiments, such as "crowded" and "unbeatable" in the "Sales staff" aspect; “fierce” and “long in the “Cashier section” aspect; as well as "maintained", "comfortable", and "spacious" in the "Parking attendant" aspect which is more appropriate to include in parking facility opinions.

4.5. Utilizing the result for human resource development

The results of the online review analysis produced by the proposed method can be used as a basis for human resource development. One of the results of the analysis is the aspects of human resources that are most criticized by customers, either positively or negatively, which are shown in the Pareto graph. In this case study, the human resource aspects that are criticized a lot by customers come from frontline employees, including the cashier section, sales staff, security staff, and parking attendants. Management can use this knowledge to determine which areas of employees require further development to serve customers better. For example, the cashier section is the section that has the most negative comments from customers. Negative comments about cashiers are dominated by customers who feel that the cashier's service is unfriendly and slow, which can cause long cashier queues. Management can design a training program for cashiers in serving customers. Of course, an appropriate training program design is needed to produce good employee performance after training (Diamantidis & Chatzoglou, 2014).

In addition to training programs, the proposed method can be used to periodically monitor customer online reviews on various platforms. It is hoped that this periodic monitoring can be seen by employees directly so that it can be a driving force in providing good service to customers. Marder et al. (2023) explain that frontline employees in retail will be motivated to provide better service when they recognize customers who might leave online reviews. Employees will tend to provide better service in the hope that customers will provide positive reviews and leave a good impression of the retailer.

5. RESULT AND DISCUSSION

The results of the analysis in the form of extracted aspects and sentiments can be used as a basis for evaluating the parts of work that cause the most negative assessments from customers and determining priorities for improvement or training in areas of work in the retail industry. Meanwhile, the results in the form of extracted opinions can be used as a basis for training topics for related work departments or as a basis for determining criteria or selection processes when recruiting new employees. The proposed method also succeeded in extracting aspects, sentiments, and opinions of online reviews written in Indonesian using an ABSA model trained on an English dataset. This is possible because online reviews are first translated into English using the help of LLM.

However, there are still shortcomings in the proposed method, namely the results of the translation and preprocessing processes using LLM are less consistent. When carrying out translation or preprocessing, sometimes some reviews cannot be successfully translated or have their grammar corrected. Unsuccessful translation or preprocessing processes may be caused by empty output, LLM output cannot be saved into a JSON file, and other reasons. Apart from that, the results of the analysis to extract opinions also still show inappropriate results. This is likely caused by the process of obtaining opinions using dependency rules which obtain pairs of aspects and opinions from the relationships between words according to the rules that have been defined. Apart from that, inaccurate results can also be caused because the review data being analyzed is written in less standard language so the translation results have the potential to produce translations that are less precise or even have different meanings.

6. CONCLUSION

The proposed method is successful in identifying aspects, sentiments, and opinions as a basis for developing human resources based on online review data written in Indonesian which is translated into English using LLM using the ABSA model trained with datasets in English. Even though the proposed method still has several shortcomings, the resulting analysis results can be used as a basis for developing human resources in retail based on reviews from customers. To improve the quality of analysis results, several things can be done in further research. First, using the ABSA model which is trained by adding a dataset created using the data to be analyzed so that the identified aspects can be more accurate. Second, using the aspect sentiment triplets extraction (ASTE) technique which can produce triplets in the form of aspects, sentiments, and opinions contained in the text (Jian et al., 2021).

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