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SENTIMENT ANALYSIS ON TRAINING IMPLEMENTATION'S FEEDBACK IN PT XYZ

Fadilia Rinarwastu[1*]; Imam Yuadi[2]

Magister of Human Resource Development[1], Department of Information and Library Science[2]
Airlangga University, Surabaya, Indonesia
https://pasca.unair.ac.id/
fadilia.rinarwastu-2024@pasca.unair.ac.id*, imam.yuadi@fisip.unair.ac.id
(*) Corresponding Author

Abstract—*Customer satisfaction is an important aspect in building a company's image, both for employees and external parties. In order to improve employee satisfaction and performance, training that organized by the company needs to receive feedback so that the training organizers can continue to provide the best service to employees who participate in the training. The large volume of feedback that must be processed in text form, leads to prolonged identification of comments and the omission of certain training programs from further analysis. This study applies text mining using sentiment analysis and Word Cloud visualization to evaluate the effectiveness of training methods and identify areas for improvement based on employee feedback on training programs at PT XYZ. The amount of data used after preprocessing was 48,910 open feedback responses from 4,314 training sessions consisting of three forms: classroom training, digital learning, and hybrid learning. The evaluation for clustering used the K-Means method, which turned out to use two optimal clusters based on the silhouette. Overall satisfaction with the training was determined through key points such as stable internet connection, overlapping of training schedule, and poor learning environment. Issues frequently that identified in the Word Cloud analysis revealed keywords describing positive and negative aspects of the situation that are requiring further improvement. This identification is useful for developing recommendations to enhance the implementation of the training and participants' experience. Further research may also involve advanced sentiment analysis and more accurate classification methods.*

Keywords: *feedback, k-means, sentiment analysis, training, word cloud.*

Abstrak—*Kepuasan pelanggan merupakan aspek penting dalam membangun citra sebuah perusahaan baik untuk karyawan maupun pihak eksternal. Dalam meningkatkan kepuasan dan kinerja karyawan, pelatihan yang diselenggarakan oleh PT XYZ perlu mendapat umpan balik agar penyelenggara pelatihan dapat senantiasa memberikan pelayanan terbaik kepada pegawai yang mengikuti pelatihan. Banyaknya umpan balik yang harus diproses dalam bentuk teks, menyebabkan lamanya proses identifikasi komentar dan adanya pelatihan yang terlewat untuk dianalisis lebih lanjut. Penelitian ini menerapkan text mining dengan menggunakan sentiment analysis dan visualisasi Word Cloud untuk mengevaluasi efektivitas metode pelatihan dan untuk mengidentifikasi area yang dapat ditingkatkan dari umpan balik karyawan pada program pelatihan di PT XYZ. Jumlah data yang digunakan setelah preprocessing adalah 48,910 umpan balik terbuka dari 4.314 sesi pelatihan yang terdiri dari tiga bentuk: pelatihan di kelas, pembelajaran digital, dan pembelajaran hybrid. Evaluasi untuk pengelompokan menggunakan metode K-Means yang ternyata menggunakan 2 klaster yang optimal berdasarkan skor silhouette. Kepuasan secara keseluruhan terhadap pelatihan ini berhasil diketahui dengan poin-poin penting yaitu koneksi internet yang stabil, jadwal pelatihan yang tumpang tindih, dan fasilitas belajar yang kurang baik. Masalah yang sering muncul dalam analisis Word Cloud mengungkapkan kata kunci yang menggambarkan aspek positif dan negatif dari situasi yang membutuhkan perbaikan lebih lanjut. Identifikasi ini berguna untuk mengembangkan rekomendasi untuk meningkatkan pelaksanaan pelatihan dan pengalaman peserta. Penelitian selanjutnya juga dapat melibatkan analisis sentimen tingkat lanjut dan metode klasifikasi lain yang lebih akurat.*

Kata Kunci*: umpan balik, k-means, analisis sentimen, pelatihan, word cloud.*

INTRODUCTION

Conducting training for employees is needed to improve insight, update knowledge and learn new things related to work, which can help increase company productivity by having human resources who have skills according to company needs. At PT XYZ, the implementation of training is divided into 3 methods: in class training, digital learning, and hybrid learning. In class training is a learning activity that is carried out offline and face-to-face, while digital learning is online learning which is usually carried out through Zoom Meeting or self learning through the PT XYZ learning application. PT XYZ also conducts hybrid learning where participants can attend offline and online which is more flexible for the employee to attend.

The training certainly requires evaluation as a form of feedback from participants on their experience in participating in training activities organized by the company. With today's digital developments, text-based data collection and analysis can be one approach to understanding employee perceptions of training. Analysis of the results of the open survey can be used to evaluate the training program and identify the shortcomings and strengths of the training that has been held to provide better services in the next training implementation. In analyzing the comments of employees who have participated in training programs in training evaluation, a systematic and comprehensive approach is needed so that the data can be more easily understood.

There are 5 levels of learning evaluation in PT XYZ, namely level 1 evaluation is conducted to measure participants' response to the training; level 2 evaluation to measure participants' level of knowledge, skills, attitudes, confidence, and commitment based on their participation during the learning process; level 3 evaluation to measure the application that has been done by participants when the training is completed; level 4 evaluation to measure the results of targeted performance achievement as a result of learning that has been followed by employees; while level 5 evaluation is conducted to measure the return on training investment. This research will focus on level 1 evaluation to evaluate employees' complaints, suggestions, and opinions on training implementation at PT XYZ.

The training evaluation data that is used in this paper is for training that was held by PT XYZ in 2024. From feedback in the form of sentences with a large number, a method that can speed up to get information is needed. The purpose of this study is to evaluate training feedback through text mining and sentiment analysis.

Sentiment analysis is a natural language processing (NLP) technique that identifies important patterns of information and features from a large text corpus (Lamba & Madhusudhan, 2022). This method is used to assess whether a statement or document is positive, negative, or neutral. K-means is perhaps the most widely used clustering method, and especially the best-known partitioning-based clustering method that uses centroids for cluster presentatio (Oti et al., 2021). Word clouds is a powerful data visualization technique that allows people to get easily acquainted with the content of a large collection of textual documents and identify their subject domains for a matter of seconds. Instead of reading many sentences, the content could be automatically extracted and processed, so that only the most significant terms are retained and presented in a form of a word cloud (Kalmukov, 2021). Typically, they show the most frequent words of a text as a weighted list of words in some specific spatial. Sentiment analysis can be used to understand employees' opinions on the training programme, while K-Means Clustering will be used to group the data based on specific themes or patterns. To facilitate interpretation of the results, visualisation using Word Cloud is required to provide an intuitive picture of the words that appear frequently.

One approach that can be used to process unstructured data into meaningful information that can be used as a reference for decision making. Unstructured data can be in the form of comments or feedback, so sentiment analysis is needed to identify opinions from a text. Text mining is the semi-automated process of extracting patterns (useful information and knowledge) from large amounts of unstructured data sources (Sharda et al., 2024). Based on research by Ulya et al. (2022), the use of text mining can be used to evaluate the experience of digital application users, one of which is the Tokopedia application through the Google Play Store. In the study conducted, comment data and ratings given by users on reviews on the Google Play Store were analysed using sentiment analysis by giving positive and negative labels and making comparisons of dataset modelling using Naïve Bayes, Decision Tree and Deep Learning which were then found that the accuracy results were between 84%-90%, making it possible to be used as analytical research in the future.

Another similar research was also conducted by Firdausy et al. (2023) who also used sentiment analysis to evaluate reactions to e-learning implementation by comparing the performance of Naïve Bayes, Support Vector Machine and Deep Learning algorithms, where reactions in the form of comments were classified into 3 categories, namely appreciation, suggestions and criticism. From the

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results of the study, it is known that the Naïve Bayes model in this case study has better performance than SVM and Deep Learning with an accuracy rate of 82.54%, precision of 68.08%, and 69.81%. Implementation of K-Means for clustering was used in study by Zhou et al. (2025) about public's perception and sentiment towards palliative care in China with three cluster which are patients' physical and mental condition, disease knowledge, and nursing service.

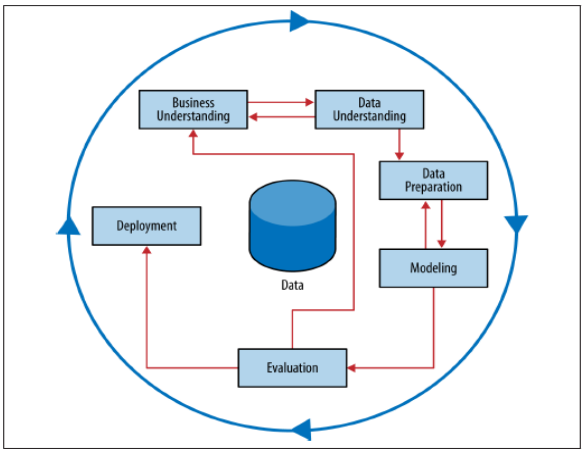
There are many methods to analyze text mining with sentiment analysis, one of which can use the classification method if the study aims to determine the classification based on certain patterns or themes from the comment/document data to be analyzed. Kumar & Meera (2022) analyzed microblogging data using data from Twitter, where sentiment analysis only uses 2 groups, namely positive and negative. This study shows that sentiment analysis using K-Means Clustering produces varying accuracy depending on the k-value used. Meanwhile, Andrianus et al. (2023), implemented the K-Means algorithm to analyze public opinion regarding the 2024 election forecast on Twitter. This study uses 1000 data from Twitter which is tested using the silhouette coefficient with an accuracy result of 0.981263 and it is also known that there are 92.50% neutral sentiment analysis, 4.30% positive, and 3.20% negative.

Based on some previous research, unstructured data such as survey results or open comments can be analyzed using text mining through sentiment analysis. From sentiment analysis, the data that has been processed can be further analyzed through clustering methods or methods for prediction using models such as SVM, Deep Learning, Random Forest, etc. In this research, the data will be analyzed through sentiment analysis by finding appropriate clusters for the sentiment and keywords generated, as well as to find out the keywords that often appear from the trainees' responses.

The result of this study will be used to develop the training method, improve the services of the training implementation, and follow up on participant complaints about the training program to give the best services in the future, by knowing the positive and negative keywords of the comments made by the learning participants. If the service of the training program is improved, hopefully the willingness of learning of the employee will increase too.

MATERIALS AND METHODS

Cross Industry Standard Process for Data Mining (CRISP-DM) is an industry-independent process model for data mining that consists of six iterative phases from business understanding to deployment (Schröer et al., 2021). The whole process is data exploration and by iterating the team or researchers can find out many things so that subsequent iterations can provide more detailed, accurate information and reduce debugging.



Source: (Plotnikova, et al. 2022)
Figure 1. The CRISP Data Mining Process

There are 7 steps in CRISP Data Mining Process (Figure 1), including business understanding, data understanding, data preparation, modeling, evaluation, and deployment. The tools that used in this research is by using Orange Data Mining.

Business Understanding

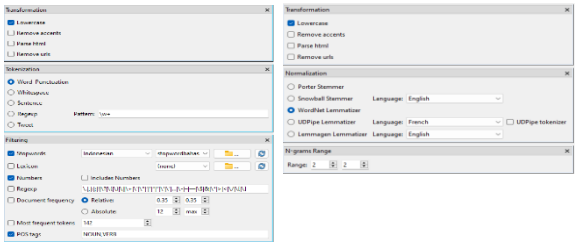
This study discusses the level 1 evaluation of training in PT XYZ that measures employee responses to training organized by the company, which classified into 3 types of training that consist of in class training, digital learning, and hybrid learning. In this evaluation there are open comments from participants so that further analysis of the grouping of comments is needed so that it can be used for further training follow-up.

Data Understanding

The data used for this study is level 1 evaluation data from all training organized by PT XYZ in 2024. In level 1 evaluation data, the data used is on open comments, where participants can express their opinions regarding their experience after attending the training organized by PT XYZ, so text mining techniques are needed to help understand all the responses given by employees. The data collected was 60,051 responses to open comments from 4,314 training courses.

Data Preparation

In data preparation, there are several processes carried out to convert text into more structured data. The process in data preparation includes data integration by preparing evaluation data which is then processed by performing (1) transformation, which is by changing all comment data in lowercase; (2) tokenization using word punctuation, which is by breaking the text into smaller units so that the text structure can be more easily understood; (3) filtering by using stopwords, eliminating numeric forms, and not using POS tags; (4) normalization with WordNet Lemmatization, which can be used to change a continuous feature to fall within a specified range while maintaining the relative differences between the values for the features (Kelleher et al., 2020); (5) N-gram range, to break sentences into 2 syllables. Preprocessing consists of data cleansing (removing URL, hashtag, and emoji, also changing all the words into lowercase, tokenizing by cutting sentences based on the constituent words, and word normalization (Nurmawiya & Harvian, 2022). Figure 2 shows the menu of Preprocess Text in Orange Data Mining. The final amount of data used after preprocessing was 4.314 training with 48,910 total responses.

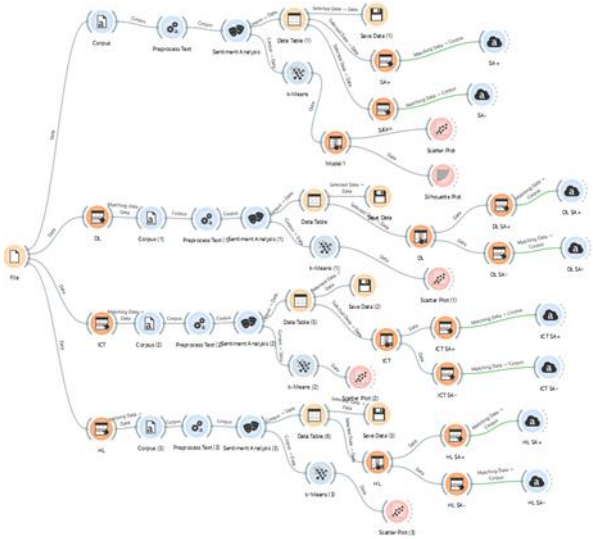


Source: (Research Results, 2025)

Figure 2. Preprocess Text

Modeling

After performing data preparation, a model was developed to identify sentiment analysis from open comments. In this model, the analysis is based on the whole data, which is then re-analyzed based on the type of training, namely in-class training (ICT), digital learning (DL), and hybrid learning (HL). (1) The first model was developed to determine the overall sentiment analysis of all types of training implementation, where analysis was conducted again to clarify the clusters using the K-Means method and using Word Cloud as a visualization to determine the word patterns in each cluster; (2) The second to fourth models are modeling for sentiment analysis of data on each type of implementation, namely the second model analyzes responses to digital learning, the third model analyzes responses to in class training, while the fourth model is used to analyze responses to hybrid learning implementation. As in the first model, clustering and the use of Word Cloud were also analyzed to find out the patterns and words that often appear in each training program. This modeling process is shown in Figure 3, which was created using Orange Data Mining.



Source: (Research Results, 2025)

Figure 3. Modeling

Evaluation

Evaluation is done by using clustering using the K-Means method. K-Means is an unsupervised machine learning method that explores potential patterns or themes in textual data to find essential themes (Zhou et al., 2023). K-means is chosen for its straightforwardness, effectiveness, and proven success in grouping data without preset categories, allowing for the assessment of word similarities and offering a summary of the corpus content (Ozturk & Tocoglu, 2025). To identify patterns and ensure the clustering of the analyzed comments, K-means can be used to quickly analyze large data sets and help determine the appropriate number of clusters through silhouette scores. Through this clustering, the data will be tested by looking at the silhouette score between the number of clusters 2 to 6. The initialization process is carried out using random initialization with iterations run 10 times with a maximum of 300 iterations for the cluster search process in one repetition (shown in Figure 4).

Deployment

Output data from sentiment analysis and data on each cluster that has been formed will be collected and used as a reference for improvement and development of training programs to be held in the following year, especially for the same training title. The model can be reused to evaluate the next training implementation by reloading the File widget.

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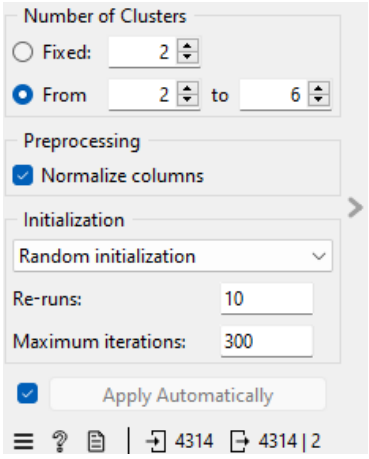


Source: (Research Results, 2025)
Figure 4. K-Means

RESULTS AND DISCUSSION

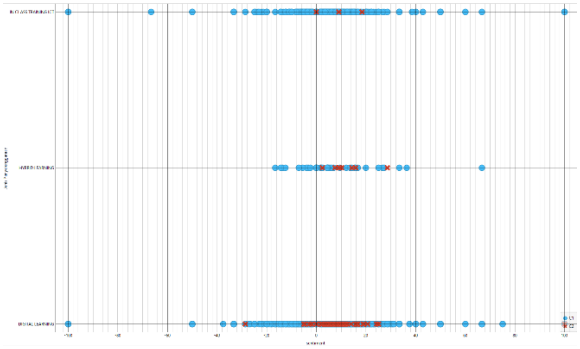
Level 1 evaluation data regarding the responses of employees who participated in training at PT XYZ in 2024. The final amount of data used after preprocessing was 4314 training with 48,910 total responses. Model 1 uses all training data, while model 2 is digital learning with 3,608 training sessions and 39.556 respondents, model 3 is in-class training with 644 training sessions and 8.040 respondents, and model 4 is hybrid learning with 62 training sessions and 1.314 respondents. Sentiment analysis was conducted using multilingual sentiment method in Indonesian language. Through sentiment analysis in Orange application for each model in Figure 3, the number of positive sentiment values (>0), negative sentiment (<0), and neutral values (0) can be found in Table 1, as well as the distribution of data contained in Figure 5 shows that the results of sentiment analysis in text mining as a whole depicted in model 1 are spread from negative to positive values.

Table 1. Sentiment Analysis

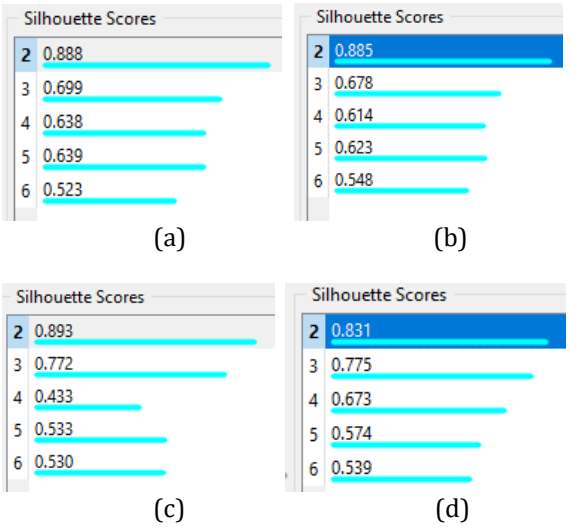
Sentiment Analysis	Model 1	Model 2	Model 3	Model 4
Positive Value	2.004	1.640	330	17
Negative Value	561	431	121	1
Neutral Value	1.749	1.537	193	44

Source: (Research Results, 2025)

From the results of sentiment analysis, clustering testing is carried out to get the most optimal number of clusters based on the silhouette score with a range of 2 to 6 clusters. Silhouette scores are used to evaluate the quality of clusters in cluster analysis by measuring the similarity of the objects. Score that close to 1 indicates that the data point closely matches the assigned cluster (Astuti et al., 2023). In the process, it is known that the most optimal silhouette score in model 1, model 2, model 3, and model 4 is to use 2 clusters, namely model 1 with a score of 0,888; model 2 with a score of 0,885; model 3 with a score of 0,893; while for model 4 with a score of 0,831, see Fig. 6.

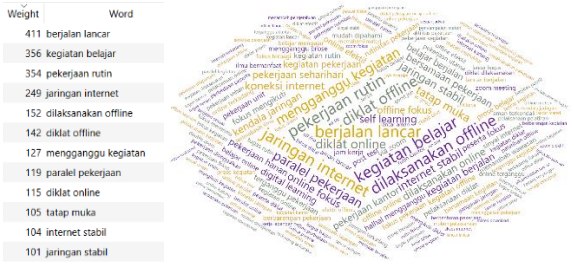


Source: (Research Results, 2025)
Figure 5. Scatter Plot of Sentiment Analysis to Types Training Program

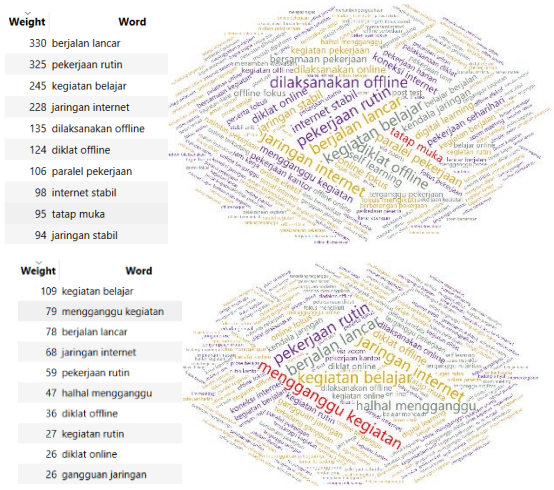


Source: (Research Results, 2025)
Figure 6. Silhouette Score: (a) Model 1; (b) Model 2; (c) Model 3; (d) Model 4

To find out the output of important words that have been processed through sentiment analysis, this study re-analyzes using Word Cloud where grouping is taken based on positive and negative values and keywords are taken based on the weight of words that often appear.



(a)



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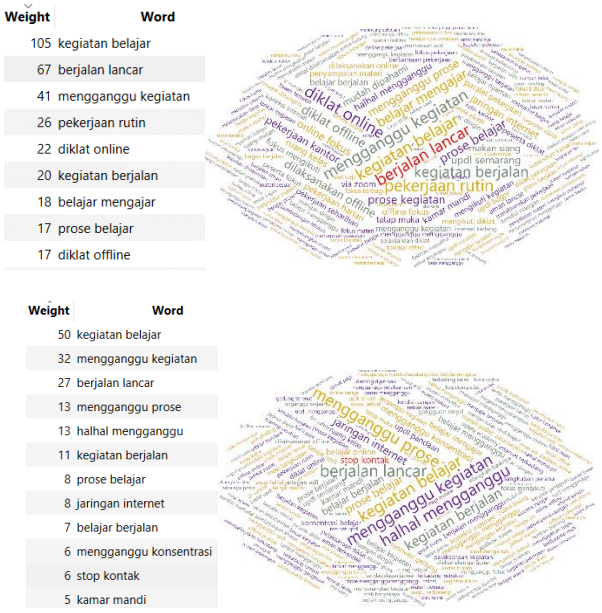

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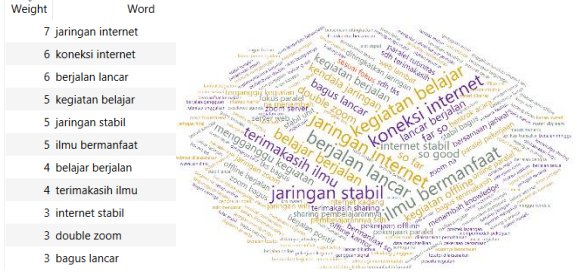

(d)

Source: (Research Results, 2025)

Figure 7. Word Cloud of Sentiment Analysis (a) Model 1: positive (upper), negative (below); (b) Model 2: positive (upper), negative (below); (c) Model 3: positive (upper), negative (below); (d) Model 4: positive (upper), negative (below)

Based on the results of the Word Cloud on Figure 7, several keywords can be identified in the overall training implemented as well as keywords for each type of training program implementation that has been implemented in 2024. Keywords contained in Table 2 are the result of manual filtering by selecting words in the Word Cloud in each model that reflect words of affirmation and criticism and employee complaints about the implementation of training based on the weighting in the Word Cloud.

Table 2. Word Cloud for Each Models

Model	Positive	Negative
Model 1 (All Training Program)	berjalan lancar internet stabil jaringan stabil peserta fokus menambah wawasan mudah dipahami aman lancar ilmu bermanfaat lancar kegiatan bagus materi bagus lancar jaringan sinyal stabil	mengganggu kegiatan hal-hal mengganggu gangguan jaringan kendala jaringan terganggu pekerjaan online terganggu internet lambat bersamaan pekerjaan mengganggu fokus terganggu jaringan meninggalkan pekerjaan terganggu kerjaan gangguan sinyal
Model 2 (Digital Learning)	berjalan lancar internet stabil jaringan stabil online fokus online efektif fokus mengikuti lancar berjalan ilmu bermanfaat mudah dipahami lancar jaringan berjalan positif alhamdulillah lancar sesuai jadwal	mengganggu kegiatan hal-hal mengganggu gangguan jaringan koneksi internet terganggu pekerjaan terkadang gangguan online terganggu terganggu rutinitas internet lambat bersamaan kegiatan pembelajaran terganggu paralel kegiatan fokus terganggu terkendala jaringan zona berbeda internet hilang susah mengikuti

Model	Positive	Negative
		mengalami gangguan
		menganggu
		kelancaran
Model 3 (In Class Training)	berjalan lancar	mengganggu
	mudah	kegiatan
	dipahami	mengganggu proses
	ruang kelas	hal-hal mengganggu
	kamar mandi	mengganggu
	makan siang	konsentrasi
	offline fokus	stop kontak
	belajar nyaman	kamar mandi
	ac dingin	koneksi internet
	ruangan dingin	renovasi gedung
	kebersihan	ruangan dingin
	kamar	jaringan wifi
	lancar kegiatan	gangguan sinyal
	materi sesuai	materi padat
	nyaman belajar	ac ruangan
	memahami	kelas panas
	materi	siswa mengantuk
	mudah	kursi pijat
	dimengerti	ketidakjelasan jadwal
	berjalan aman	kertas buram
	menambah	kendala gangguan
	wawasan	mess wifi
	terimakasih	akses internet
	updl	udiklat ke bandara
	fokus belajar	kegiatan padat
	berjalan positif	dinding diperbaiki
	lancar bagus	redup redup
	bagus kegiatan	lampu kedip kedip
	ac ruangan	stop kontak lantai
	materi	mengganggu
	menyenangkan	membahayakan
	fasilitas mess	kelas kotor
	menu makan	posisi kursi
	lancar fasilitas	berisik mengganggu
		pintu kamar mandi
Model 4 (Hybrid Learning)	jaringan	terkadang gangguan
	internet	gangguan zoom
	berjalan lancar	akses jaringan
	jaringan stabil	jaringan internet
	ilmu	ac dingin
	bermanfaat	area wisma
	terima kasih	kurang memadai
	internet stabil	kendala jaringan
	bagus lancar	jaringan bandwidth
	lancar berjalan	peningkatan kualitas
	bagus	kualitas pelayanan
	stabil bagus	pelayanan bagus
	bagus	web lambat
	terimakasih	
	terimakasih	
	sharing	
	menambah	
	knowledge	
	ditingkatkan	
	jaringan zoom	
	berjalan positif	

Source: (Research Results, 2025)

In the sentiment analysis results, it was found in the overall training in 2024. There were positive comments such as the activities running smoothly and stable internet, but there were also negative comments related to disruptive conditions, obstacles when learning online, and training that collided with routine work. From model 1, to make it easier to understand the advantages and disadvantages of each type of training program implementation, model 2, model 3, and model 4 were created. Model 2, which is for training with digital learning, is known for some participants to have a positive experience of the network conditions, the knowledge provided, and the appropriate schedule. In addition, some digital learning participants also complained about the internet network, training that was interrupted by routine work so that focus was disrupted, and the existence of different time zones between participants due to different locations. In model 3, which is in-class training, the keywords taken in addition to verbs are nouns because they are related to the training facilities. It is known that participants give positive comments on the smoothness of the activities, the convenience of learning offline (face-to-face), the material that is easy to understand and some facilities such as meals, air conditioning, and lodging facilities. However, in the negative sentiment, it is also known that there are some complaints about facilities such as power outlets, bathrooms, dirty floors, chair positions, and internet networks so that further evaluation is needed to make improvements to training facilities. In model 4, which is for training with hybrid learning, it is known that participants are satisfied with the internet network, useful sharing, and smooth activities. However, there were participants who also complained about the quality of service, the slow web, and the internet network of the training venue. The analysis of the hybrid learning model yielded fewer results than in-class training and digital learning. This was due to the amount of training data collected by PT XYZ in 2024 for each type, with only 62 training sessions, compared to 644 in-class training sessions and 3,608 digital learning sessions. Participants' comments are more diverse in in-class training because it is conducted face-to-face, resulting in a lot of feedback related to the training facilities. Meanwhile, in digital learning and hybrid learning, participants' comments are not as diverse because the complaints are limited to personal internet connections and participants' lack of focus due to not being able to leave their work.

The model that has been created in this study needs to be further evaluated because there are keywords that are positive words but enter the negative group and vice versa, so that manual analysis and sorting are still needed to get more optimal results. This discrepancy between the grouping of negative and positive words may be due to the use of multilingual sentiment analysis built into Orange Data Mining, resulting in a less effective level of word sensitivity. Nurcahyawati & Mustaffa (2023) researched customer sentiment detection using the Vader Lexicon and found the limitations in

the effectiveness of the Vader lexicon for annotation due to the incompleteness of word dictionaries and applied word weights. Although the word underwent normalization, not all normalized words are included in the lexicon and make some words that should have weighted values to produce an opinion not to be detected, resulting in no weighted value. The study conducted by Fauziah et al. (2021), discusses trends in lexicon-based sentiment analysis research in Indonesian, and the study shows that the lexicon-based approach has limitations in handling multi-word and idiomatic phrases that are common in Indonesian, as most lexicon dictionaries only cover single words, so the contextual meaning of phrases or idioms is not always accurately detected.

This study can still be developed by using other sentiment analysis methods that are more accurate than multilingual sentiment by using custom dictionary then look for more reference data sources for positive and negative words. The clustering method can also be further explored by comparing other clustering methods to find out which method can produce output with the most optimal accuracy in accordance with business understanding.

CONCLUSION

This study investigates text mining techniques using sentiment analysis based on employee feedback on training programs held by PT XYZ in 2024. Analysis was conducted on 4,314 training sessions consisting of in-class training, digital learning and hybrid learning to identify sentiments and patterns from the comments given by employees. The findings reveal positive feedback regarding the smooth execution of training sessions, effective learning materials, and stable internet in certain cases. The challenges were also noted, such as network connectivity issues during online and hybrid sessions, disruptions from overlapping work schedules, and facility inadequacies in in-class training. These insights offer valuable guidance for enhancing training programs to better meet employee expectations and organizational goals.

The study contributes to the field by demonstrating how sentiment analysis and clustering methods can transform unstructured textual data into actionable insights, but limitations were observed, such as the need for manual refinement of keyword classifications and the inherent challenges of multilingual sentiment analysis. For practical contribution, this study can be used to early detection for positive and negative responses to speed up follow-up actions and this study can be used as reference for better research of sentiment analysis for academic contribution. Future research could explore the integration of more advanced sentiment analysis models and alternative clustering techniques to improve the accuracy and granularity of results. The predictive model from this study can also be developed by comparing algorithms from supervised learning (such as Naïve Bayes or Support Vector Machine) to predict positive and negative comments from the training program at PT XYZ. Additionally, further studies could focus on longitudinal evaluations of training programs to assess the long-term impact on employee performance and organizational productivity.

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