JURSIMA
Jurnal Sistem Informasi & Manajemen
ISSN : 2338-1523, E-ISSN: 2541- 576X

MEASURING EMPLOYER BRANDING AWARENESS THROUGH NET BRAND REPUTATION EVALUATION BASED ON SOCIAL MEDIA SENTIMENT ANALYSIS

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Abstract

Employer branding plays an important role in shaping a company's image and attracting high-quality employees. However, evaluating a company's reputation among internal and external stakeholders remains challenging. This study examines employer branding awareness through social media mentions using sentiment analysis of Instagram comments on PT Angkasa Pura I's official account (@ap_airports). Unlike survey-based approaches, this study utilizes unconditioned public sentiment data to assess brand reputation. Sentiment analysis was conducted using Bidirectional Encoder Representations from Transformers (BERT) with a pre-trained IndoBERT model following the CRISP-DM research framework. The model achieved an accuracy of 88% on validation data and 98% on testing data. The findings indicate a Net Brand Reputation (NBR) score of 13.57%, suggesting that PT Angkasa Pura I's reputation remains relatively low. In 2024, positive sentiment (276 comments) only slightly exceeded negative sentiment (270 comments), with a difference of 5.2%. Meanwhile, neutral sentiment accounted for over 60% of comments, reflecting active public engagement with the company's social media. The study suggests that PT Angkasa Pura I should improve service quality, strengthen stakeholder engagement, and optimize social media interactions to enhance employer branding and encourage more positive public sentiment.

Keywords: *Employer Branding, Sentiment Analysis, Social Media Mention, Net Brand Reputation, IndoBERT*

INTRODUCTION

In today's highly competitive business environment, companies are increasingly required to establish strong organizational reputations to attract and retain high-quality human resources. Employees are considered one of the most valuable assets of a company because organizational performance is often reflected through employee competence, work ethics, and engagement. Organizations with a positive corporate image are generally more successful in attracting talented individuals and maintaining long-term employee commitment. Therefore, companies increasingly rely on employer branding as a strategic mechanism to communicate organizational values and improve perceptions among employees, prospective employees, and the general public [1].

Employer branding refers to an organization's strategic efforts to position itself as an attractive workplace by communicating values, organizational culture, and employment benefits to current and potential employees [2]. According to employer branding frameworks, this concept generally consists of three key dimensions: awareness, attraction, and experience [3]. Awareness refers to how well the public recognizes and perceives a company; attraction reflects the ability to attract competent talent; while experience describes employee perceptions and workplace satisfaction throughout the employment cycle [3].

The increasing adoption of digital platforms has transformed how organizations build and maintain employer branding. Social media platforms such as Instagram, Twitter (X), TikTok, and YouTube have become strategic communication channels that facilitate direct interaction between organizations and stakeholders [4]. Unlike traditional communication channels, social media allows unrestricted public participation where individuals freely express opinions, complaints, satisfaction, and expectations regarding organizations. These interactions produce a substantial amount of unstructured textual data, commonly referred to as social media mentions, which can serve as valuable indicators of public perception and brand reputation [5].

Social media mentions have become increasingly relevant in measuring organizational awareness because they reflect spontaneous public sentiment without controlled conditions such as surveys or interviews [6]. Conventional employer branding assessments frequently rely on employee satisfaction surveys or structured feedback mechanisms, which may be affected by response bias and limited representativeness [7]. In contrast, sentiment obtained from social media interactions provides more authentic and naturally occurring opinions that may better represent stakeholders' perceptions [8]. Consequently, social media sentiment analysis has emerged as an alternative approach for evaluating organizational reputation, customer satisfaction, and employer branding performance [9].

Sentiment analysis, also known as opinion mining, is a computational approach used to identify emotional polarity in textual content by classifying opinions into positive, neutral, or negative categories [10]. Over the past decade, sentiment analysis has been widely implemented across various domains, including healthcare, politics, financial forecasting, marketing, airline service evaluation, and public opinion measurement [11]. In organizational studies, sentiment analysis offers valuable insights into stakeholder attitudes, enabling companies to formulate evidence-based decisions for improving services, policies, and communication strategies [12].

The advancement of Natural Language Processing (NLP) technologies has significantly improved sentiment classification accuracy. Traditional machine learning algorithms such as Naïve Bayes, Support Vector Machine (SVM), and Decision Tree have been widely applied for sentiment analysis; however, deep learning-based architectures have demonstrated superior performance in capturing contextual language patterns [13]. Among these approaches, Bidirectional Encoder Representations from Transformers (BERT) has emerged as one of the most effective models due to its ability to understand contextual relationships bidirectionally, enabling more accurate language representation [14]. Unlike conventional sequential models, BERT employs a transformer architecture based on self-attention mechanisms, allowing simultaneous contextual understanding of words within sentences [15].

Several previous studies have demonstrated the effectiveness of BERT for sentiment analysis tasks. Patel *et al.* found that BERT outperformed conventional machine learning methods in analyzing customer sentiment toward airline services, achieving higher accuracy, precision, recall, and F1-score [6]. Similarly, Olabanjo *et al.* reported that BERT achieved superior performance compared to Long Short-Term Memory (LSTM) and Linear Support Vector Classifier (LSVC) in political sentiment analysis, reaching an accuracy level above 90% [7]. For Indonesian-language datasets specifically, IndoBERT, a pre-trained BERT model developed using Indonesian corpora, has shown promising performance in sentiment classification tasks due to its contextual understanding of local linguistic characteristics [16].

Despite the growing application of sentiment analysis in organizational contexts, studies examining employer branding awareness through social media mentions using sentiment analysis remain limited, particularly within the Indonesian aviation industry. PT Angkasa Pura I, one of Indonesia's largest state-owned airport operators, represents a relevant case for examining employer branding awareness. Although the company regularly conducts Employee Satisfaction and Engagement assessments, existing survey results appear inconsistent with public criticism and discussions circulating on digital platforms. Such discrepancies indicate the necessity of evaluating organizational reputation through alternative and naturally occurring data sources.

This study addresses the research gap by evaluating social media mentions as part of employer branding awareness through sentiment analysis of Instagram comments on PT Angkasa Pura I's official account (@ap_airports). Unlike survey-based assessments, this study utilizes spontaneous and unconditioned public sentiment derived from social media interactions. Sentiment classification is conducted using Bidirectional Encoder Representations from Transformers (BERT) with a pre-trained IndoBERT model following the Cross Industry Standard Process for Data Mining (CRISP-DM) methodology. In addition, this study incorporates Net Brand Reputation (NBR) measurement to quantitatively evaluate organizational reputation based on sentiment polarity [17].

The contributions of this study are threefold. First, it provides an alternative framework for measuring employer branding awareness using social media sentiment data. Second, it demonstrates the implementation of BERT-based sentiment analysis in the Indonesian employer branding context, particularly within the aviation sector. Third, it offers practical recommendations for PT Angkasa Pura I in strengthening stakeholder engagement and improving employer branding strategies based on public sentiment insights. Therefore, this research is expected to contribute theoretically to employer branding and sentiment analysis literature, while also providing practical implications for organizational decision-making and reputation management.

RESEARCH METHODS

This study employed a quantitative approach using sentiment analysis to evaluate employer branding awareness through social media mentions associated with PT Angkasa Pura I. The research focused on analyzing public sentiment expressed in Instagram comments posted on the company's official account (@ap_airports) as an alternative measurement of employer branding awareness. Unlike conventional survey-based approaches, this study utilized naturally occurring sentiment data collected from social media interactions to reduce response bias and obtain a more authentic representation of stakeholder perceptions.

The study adopted the Cross Industry Standard Process for Data Mining (CRISP-DM) framework as the primary research methodology. CRISP-DM was selected because it provides a structured and systematic process for data mining and machine learning implementation, consisting of six stages: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. The framework has been widely applied in sentiment analysis and data-driven research because of its flexibility and methodological consistency.

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This research followed the six stages of the CRISP-DM framework to systematically evaluate employer branding awareness through sentiment analysis. The overall research workflow is illustrated in Fig. 1.

A. Business Understanding

The first stage focused on identifying the research problem and determining research objectives. PT Angkasa Pura I, as one of Indonesia's largest state-owned airport operators, requires a reliable mechanism to evaluate its employer branding awareness. Existing employee satisfaction and engagement surveys were considered insufficient due to potential response bias and inconsistency with public criticism found on digital platforms.

Therefore, this study aimed to assess employer branding awareness through social media mentions, specifically by analyzing Instagram comments to identify public sentiment toward the company. The study sought to answer the following research objectives:

1. To evaluate the performance of sentiment analysis using the Bidirectional Encoder Representations from Transformers (BERT) model.
2. To measure the company's reputation using the Net Brand Reputation (NBR) metric.
3. To identify dominant public sentiments and recurring discussion themes in social media interactions.
4. To assess employer branding awareness based on social media sentiment.

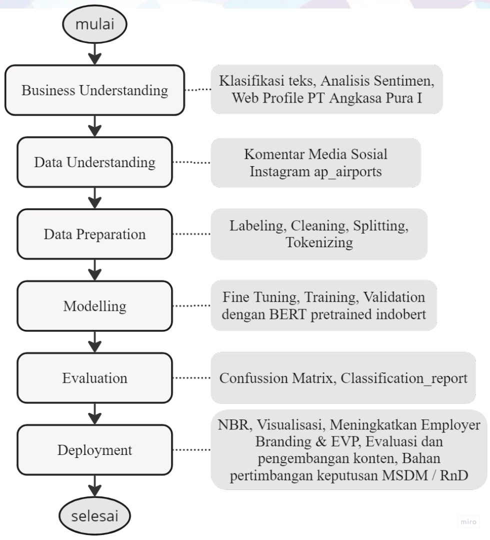

Figure 1 – Research Workflow

B. Data Understanding

The dataset consisted of Instagram comments collected from PT Angkasa Pura I's official Instagram account (@ap_airports). Data collection covered comments posted between January 20, 2016, and April 25, 2024.

More than 50,000 Instagram comments were obtained, containing opinions by users regarding airport services, organizational policies, employee interactions, pricing, and public experiences related to PT Angkasa Pura I. Since social media comments contain unstructured textual information, an exploratory analysis was conducted to understand data characteristics, including comment distribution, language patterns, noise, and sentiment tendencies.

At this stage, preliminary examination was also conducted to identify irrelevant comments, duplicated text, missing values, spam content, and promotional messages that could affect model performance.

C. Data Preparation

Data preparation involved several preprocessing stages to ensure data quality and model readiness. The preprocessing workflow included:

1) Data Labeling

Since manually labeling over 50,000 comments would require substantial time and cost, sentiment labeling was performed automatically using a pre-trained sentiment classification model, namely mdhugol/indonesia-bert-sentiment-classification, which is based on IndoBERT (indobenchmark/indobert-base-p1).

The comments were classified into three sentiment categories:

- Positive: comments reflecting satisfaction, appreciation, or favorable opinions;
- Neutral: comments containing objective statements, general information, or responses unrelated to emotional evaluation;
- Negative: comments reflecting complaints, dissatisfaction, criticism, or negative experiences.

Special consideration was given to giveaway-related comments or comments intended solely to fulfill social media participation requirements, which were predominantly categorized as neutral sentiment.

2) Data Cleaning

Data cleaning was performed to eliminate unnecessary information and improve text quality before model training. This process included:

- removing duplicated comments,
- eliminating emojis, symbols, URLs, and punctuation,
- removing irrelevant characters,
- handling missing values,
- converting text into lowercase format,
- eliminating noisy and irrelevant text.

The cleaning process was essential to reduce bias and improve contextual understanding during sentiment classification.

3) Dataset Splitting

The labeled dataset was divided into training, validation, and testing datasets to evaluate model generalizability. The dataset split was conducted proportionally to ensure balanced sentiment representation across all categories.

The training dataset was used for model learning, the validation dataset was used to optimize hyperparameters and monitor training performance, while the testing dataset was utilized to evaluate final classification performance.

4) Tokenization

The cleaned textual data were transformed into machine-readable numerical representations using the BERT tokenizer (BertTokenizer). Tokenization converted textual input into tokens and generated numerical embeddings compatible with the transformer architecture.

Special tokens such as [CLS] and [SEP] were included as required by the BERT model. The tokenization stage enabled contextual embedding generation while preserving semantic relationships among words.

D. Modeling

The modeling phase employed Bidirectional Encoder Representations from Transformers (BERT) using the pre-trained IndoBERT model for Indonesian-language sentiment classification.

BERT was selected because of its superior capability in understanding bidirectional contextual relationships between words compared to conventional

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Jurnal Sistem Informasi & Manajemen
ISSN : 2338-1523, E-ISSN: 2541- 576X

machine learning methods. The transformer architecture enables contextual representation learning through self-attention mechanisms, allowing sentiment prediction to consider both preceding and succeeding textual contexts.

The study applied a fine-tuning approach, where the pre-trained IndoBERT model was adapted to the sentiment classification task. During training, model hyperparameters were adjusted to optimize classification performance for Indonesian Instagram comments.

The classification task involved predicting three sentiment classes:

- Positive
- Neutral
- Negative

where the sentiment output represented the emotional polarity of each Instagram comment.

E. Evaluation

Model evaluation was conducted using a Confusion Matrix and classification performance metrics, including:

- Accuracy
- Precision
- Recall
- F1-score

Accuracy measures the proportion of correctly classified instances relative to the total dataset:

$$\text{Accuracy}=\frac{Number\ of\ correct\ predictions}{Number\ of\ predictions} \quad (1)$$

Precision measures the proportion of correctly predicted positive instances:

$$\text{Precision}=\frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{TP_i+FP_i} \quad (2)$$

Recall evaluates the model's ability to identify actual sentiment classes correctly:

$$\text{Recall}=\frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{TP_i+FN_i} \quad (3)$$

F1-score represents the harmonic mean of precision and recall:

$$\text{F1}=\frac{1}{N}\sum_{i=1}^{N}\frac{2\ x\ Precision_i\ x\ Recall_i}{Precision_i\ x\ Recall_i} \quad (4)$$

Where:

N = Total Class
TP = True Positives
TN = True Negatives
FP = False Positives
FN = False Negatives

Additionally, the Net Brand Reputation (NBR) metric was calculated to measure organizational reputation based on sentiment polarity. NBR quantifies the difference between positive and negative sentiment relative to total sentiment volume.

$$\text{NBR}=\frac{Positive\ Mention-Negative\ Mention}{Positive\ Mention+Negative\ Mention}x10 \quad (5)$$

A higher NBR value indicates a stronger positive reputation, while a lower or negative value reflects weaker public perception.

F. Deployment

The final stage involved interpreting sentiment analysis results and visualizing public opinion trends regarding PT Angkasa Pura I. Visualization techniques such as sentiment distribution analysis, and word clouds were employed to identify dominant discussion topics and frequently occurring keywords.

The deployment phase also focused on generating managerial insights to support PT Angkasa Pura I in improving employer branding awareness, customer engagement, service quality, and organizational communication strategies through social media platforms.

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RESULTS AND DISCUSSIONS

The Results and Discussion section is explained based on the research stages already outlined. This uses the CRISP-DM flow, which begins with Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment.

A. Business Understanding

The primary objective of this study was to evaluate employer branding awareness through social media mentions using sentiment analysis of Instagram comments associated with PT Angkasa Pura I's official account (@ap_airports). Unlike conventional employee satisfaction surveys, this study utilized naturally occurring public sentiment expressed through social media interactions. Such an approach provides a broader and less biased understanding of stakeholder perceptions regarding organizational reputation.

The implementation of sentiment analysis was intended not only to classify public opinions into positive, neutral, and negative categories but also to measure the company's reputation quantitatively through the Net Brand Reputation (NBR) metric. Furthermore, this study aimed to identify recurring sentiment patterns and dominant public concerns reflected in Instagram comments.

B. Data Understanding

The dataset consisted of Instagram comments collected from PT Angkasa Pura I's official Instagram account (@ap_airports), covering interactions between January 20, 2016, and April 25, 2024. More than 50,000 comments were obtained, representing diverse stakeholder perspectives related to airport services, pricing, facilities, customer experience, complaints, and organizational performance.

Initial exploratory analysis indicated that Instagram comments varied substantially in length, writing style, and emotional expression. Since the data originated from social media, substantial textual noise was observed, including emojis, abbreviations, informal language, duplicated comments, promotional content, hyperlinks, and giveaway-related messages. Therefore, preprocessing was required to improve text quality before sentiment classification.

Preliminary findings suggested that public discussions mainly revolved around airport services, customer complaints, ticket pricing, travel experiences, and operational information.

C. Data Preparation

1) Data Labeling

The data labeling process categorized Instagram comments into positive, neutral, and negative sentiment classes. Due to the large volume of comments exceeding 50,000 records, manual annotation was considered impractical in terms of time and cost. Therefore, automatic labeling was implemented using the pre-trained model mdhugol/indonesia-bert-sentiment-classification, based on the IndoBERT architecture.

The labeling results indicated that neutral sentiment dominated the dataset, reflecting the prevalence of informational comments, general interactions, and giveaway participation comments. Positive comments generally expressed appreciation for airport services, facilities, and employee responsiveness, whereas negative comments mostly involved complaints related to service quality, pricing, delays, facilities, and customer dissatisfaction.

Special attention was given to giveaway-related comments, as many users interacted with social media content solely to fulfill campaign requirements. Since these comments rarely contained explicit emotional expressions, they were predominantly categorized as neutral sentiment.

2) Data Cleaning

The cleaning process was conducted to improve dataset consistency and reduce classification noise. This stage included duplicate removal, punctuation elimination, text normalization, lowercase conversion, hyperlink deletion, symbol removal, and irrelevant content filtering.

Before preprocessing, many comments contained excessive punctuation, emojis, hashtags, repeated characters, and informal abbreviations commonly found in Indonesian social media communication. After cleaning, textual consistency improved significantly, enabling the model to capture semantic relationships more effectively.

The preprocessing stage was essential because transformer-based models rely heavily on contextual understanding. Noisy textual patterns may reduce sentiment prediction accuracy and introduce bias into the classification process.

3) Dataset Splitting and Tokenization

After preprocessing, the dataset was divided into training, validation, and testing subsets to evaluate model robustness and generalization capability. This partition ensured that the model could learn sentiment patterns from training data while maintaining objective performance evaluation through independent testing data.

4) Tokenization

Tokenization was applied using BERT Tokenizer (BertTokenizer) to convert textual comments into machine-readable token representations. The tokenizer transformed sentences into contextual embeddings while preserving semantic dependencies between words. Additional special tokens such as [CLS] and [SEP] were incorporated to align with BERT input requirements.

D. Sentiment Classification Modeling

The sentiment classification process employed the Bidirectional Encoder Representations from Transformers (BERT) architecture using the pre-trained IndoBERT model. The model underwent a fine-tuning process to adapt contextual language understanding to the characteristics of Indonesian Instagram comments.

The selection of BERT was motivated by its capability to capture bidirectional contextual meaning, enabling improved sentiment prediction compared with conventional machine learning approaches. Through self-attention mechanisms, BERT can interpret contextual relationships among words within comments more comprehensively.

During training, the model demonstrated progressive improvement in classification performance across epochs. Validation performance indicated stable learning behavior with no significant indication of overfitting, suggesting that the model generalized effectively to unseen data.

The comparison between predictions before and after fine-tuning revealed substantial improvements in classification quality, particularly in distinguishing ambiguous neutral comments from positive and negative sentiment categories.

E. Model Evaluation

JURSIMA
Jurnal Sistem Informasi & Manajemen
ISSN : 2338-1523, E-ISSN: 2541- 576X

Model evaluation was conducted using a Confusion Matrix and several performance metrics, including accuracy, precision, recall, and F1-score. Confusion Matrix was shown in Figure 2, while the perfomance metrics results was shown in Table 1.

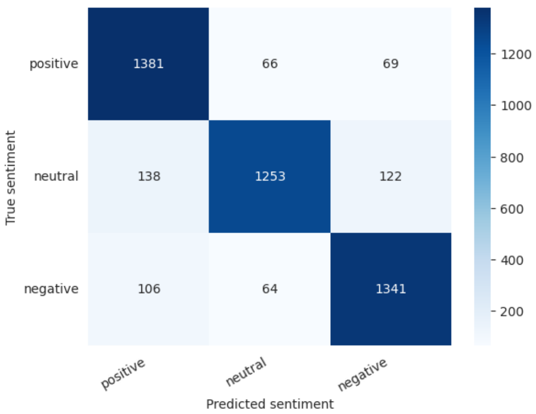

Figure 2 – Confusion Matrix Validation Data

Table 1 – Performance Metrics Results Validation Data

	Precision	*Recall*	*F1-score*	*Support*
Positive	0.85	0.91	0.88	1516
Neutral	0.91	0.83	0.87	1513
Negative	0.88	0.89	0.88	1511
Accuracy			0.88	4540
Macro avg	0.88	0.88	0.88	4540
Weighted avg	0.88	0.88	0.88	4540

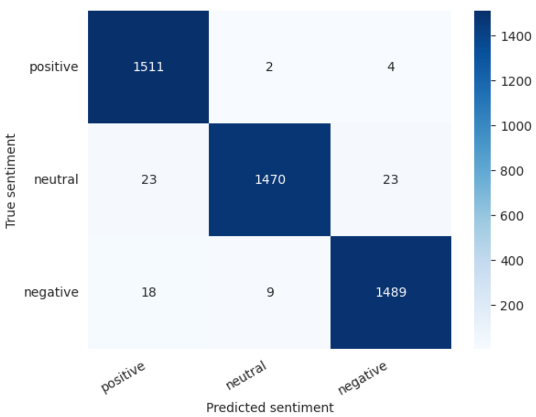

Figure 3 – Confusion Matrix Test Data

Table 2 – Performance Metrics Results Test Data

	Precision	*Recall*	*F1-score*	*Support*
Positive	0.97	1.00	0.98	1517
Neutral	0.99	0.97	0.98	1516
Negative	0.98	0.98	0.98	1516
Accuracy			0.98	4549
Macro avg	0.98	0.98	0.98	4549
Weighted avg	0.98	0.98	0.98	4549

The results demonstrated that the sentiment classification model achieved an accuracy of 88% on validation data and 98% on testing data, indicating strong classification capability. These findings suggest that the IndoBERT model effectively learned sentiment patterns from Indonesian-language social media comments.

The high testing accuracy indicates that contextual language representation significantly contributed to prediction reliability. Furthermore, precision and recall values showed balanced classification performance across sentiment classes, while the F1-score reflected strong consistency between predictive precision and sensitivity.

Compared with previous sentiment analysis studies utilizing conventional machine learning algorithms such as Support Vector Machine (SVM) and Naïve Bayes, the BERT-based approach demonstrated superior contextual understanding, particularly in handling informal language, abbreviations, and context-sensitive Indonesian expressions.

The findings support previous studies that reported the superiority of transformer-based architectures for sentiment analysis, especially in social media environments characterized by highly unstructured textual data.

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ISSN : 2338-1523, E-ISSN: 2541- 576X

To evaluate organizational reputation quantitatively, this study employed the Net Brand Reputation (NBR) metric. The NBR calculation revealed a score of 13.57%, indicating that PT Angkasa Pura I's overall reputation remains relatively low despite maintaining a slightly positive public sentiment balance.

The results showed that positive sentiment accounted for 276 comments, whereas negative sentiment reached 270 comments, resulting in only a slight difference of six comments or approximately 5.2%. This finding suggests that public perception toward PT Angkasa Pura I remains divided, where appreciation and criticism coexist simultaneously.

Although positive sentiment slightly exceeded negative sentiment, the small margin indicates that the company still faces substantial reputational challenges. Public criticism frequently addressed issues such as service quality, airport facilities, customer dissatisfaction, operational inconvenience, and pricing concerns.

From an employer branding perspective, these findings indicate that PT Angkasa Pura I's social media awareness dimension has not yet achieved an optimal reputation level. Since awareness strongly influences employer attractiveness and stakeholder trust, improving organizational image through digital engagement becomes increasingly important.

F. Deployment

As explained in the research methods, the final stage involved interpreting sentiment analysis results and visualizing public opinion trends.

After interpreting sentiment analysis results, one notable finding of this study was the dominance of neutral sentiment, accounting for more than 60% of total comments as shown in figure 4. This result suggests that public engagement with PT Angkasa Pura I's social media account is relatively active, although much of the interaction remains informational rather than emotionally expressive.

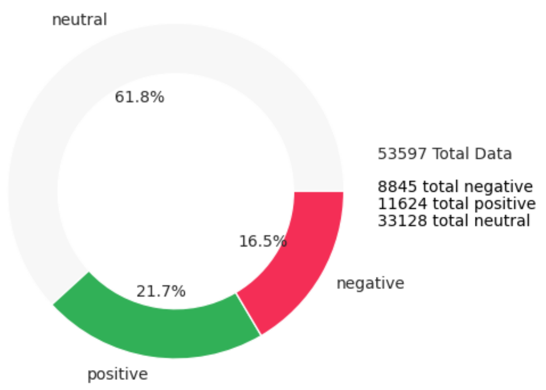

Figure 4 – Sentiment Distribution

Neutral comments primarily consisted of questions, service inquiries, travel-related information, tagging behavior, and responses to promotional activities such as giveaways. While neutral sentiment does not directly indicate positive organizational perception, it reflects high audience participation and social media visibility.

This condition presents a strategic opportunity for PT Angkasa Pura I to strengthen employer branding awareness. Effective communication strategies, timely responses to customer concerns, and more engaging digital content may gradually shift neutral sentiment toward positive sentiment.

Furthermore, complaint handling through social media should be improved because unresolved customer dissatisfaction can negatively affect organizational reputation. Social media users increasingly expect responsiveness and transparency from organizations, particularly service-oriented companies such as airport operators.

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ISSN : 2338-1523, E-ISSN: 2541- 576X

Additionally, data visualization techniques using wordclouds are used to see words that frequently appear according to the positive, negative and neutral sentiment categories.

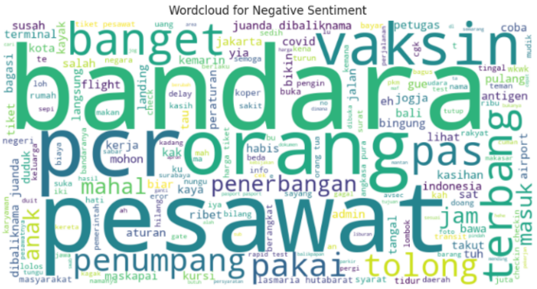

Figure 5 – Negative Sentiments Wordcloud

The negative sentiment wordcloud as shown in figure 5 indicates that public dissatisfaction was mainly driven by issues related to ticket prices, PCR testing costs, vaccination requirements, and airport services. The prominence of words such as "*mahal"* (expensive), "*PCR"*, and "*vaksin"* suggests that travel-related costs and regulatory requirements were major sources of negative perception. These findings imply that pricing policies, passenger services, and travel regulations significantly influenced the negative sentiment expressed toward PT Angkasa Pura I on social media.

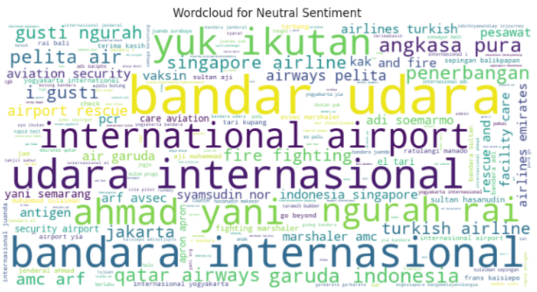

Figure 6 – Neutral Sentiments Wordcloud

The neutral sentiment wordcloud as shown in figure 6 indicates that most neutral comments were related to airport information, airline services, and promotional activities rather than emotional evaluations. The frequent occurrence of airport names, airline brands, and giveaway-related phrases suggests that users primarily engaged with PT Angkasa Pura I's Instagram account for informational purposes and campaign participation. This finding reflects a high level of social media engagement and public awareness, although such interactions do not necessarily represent positive perceptions of the organization.

Figure 5 – Negative Sentiments Wordcloud

The positive sentiment wordcloud reveals that public perceptions of PT Angkasa Pura I were predominantly associated with appreciation, optimism, and positive expectations. The frequent occurrence of words such as *semoga*, *sukses*, *keren*, and *mantap* indicates strong support and favorable evaluations of the company and its services. Moreover, the presence of airport-related terms and emotionally expressive words such as *kangen* and *keluarga* suggests that PT Angkasa Pura I has successfully created positive experiences and emotional connections with its stakeholders, contributing to a stronger organizational image and employer branding awareness.

H. Discussion

This study contributes to employer branding literature by demonstrating that social media sentiment analysis can serve as an alternative mechanism for evaluating employer branding awareness, particularly when survey-based approaches are insufficient or potentially biased.

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The findings indicate that social media mentions provide valuable real-world insights into stakeholder perceptions, allowing organizations to monitor public reputation continuously and dynamically. Unlike traditional surveys, sentiment extracted from Instagram comments reflects spontaneous and naturally occurring opinions without intervention.

The successful implementation of BERT-based sentiment analysis using IndoBERT also confirms the effectiveness of transformer architectures in Indonesian-language social media classification tasks. Given the complexity of informal Indonesian digital language, contextual language representation becomes essential for achieving reliable sentiment classification.

Practically, PT Angkasa Pura I can utilize these findings to improve stakeholder communication, optimize customer engagement, enhance service quality, and strengthen employer branding strategies. Future studies are encouraged to integrate multi-platform social media data, such as X (Twitter), TikTok, and YouTube, to provide more comprehensive employer branding evaluation.

CONCLUSION

This study evaluated employer branding awareness through social media mentions using sentiment analysis of Instagram comments collected from PT Angkasa Pura I's official account (@ap_airports). Unlike conventional survey-based approaches, this research utilized naturally occurring sentiment data from social media interactions to provide a broader and less conditioned representation of public perception toward the company.

The findings demonstrate that the implementation of Bidirectional Encoder Representations from Transformers (BERT) using a pre-trained IndoBERT model achieved strong classification performance, with an accuracy rate of 88% on validation data and 98% on testing data. These results confirm that transformer-based architectures are highly effective in analyzing Indonesian-language sentiment, particularly in social media environments characterized by informal and unstructured textual data.

Furthermore, the Net Brand Reputation (NBR) analysis yielded a score of 13.57%, indicating that PT Angkasa Pura I's reputation remains relatively low despite maintaining a slightly positive sentiment balance. Although positive sentiment slightly exceeded negative sentiment by 5.2%, the narrow difference suggests that public perception remains divided between appreciation and criticism. Major concerns identified from social media interactions included service quality, pricing, facilities, and customer experience.

Another significant finding was the dominance of neutral sentiment, accounting for more than 60% of total comments. This result reflects active public engagement with PT Angkasa Pura I's social media account and presents an opportunity for the company to strengthen employer branding awareness. By improving customer responsiveness, service quality, complaint handling, and social media communication strategies, PT Angkasa Pura I may gradually convert neutral sentiment into positive sentiment.

Theoretically, this study contributes to the growing literature on employer branding awareness and sentiment analysis by demonstrating the applicability of social media mentions as an alternative measurement approach. Practically, the findings offer strategic insights for organizations seeking to improve reputation management and stakeholder engagement through digital platforms.

Despite its contributions, this study has several limitations. First, the analysis focused solely on Instagram comments, potentially limiting the diversity of stakeholder perspectives. Second, automatic sentiment labeling may still contain classification bias despite high model performance. Therefore, future studies are encouraged to integrate multiple social media platforms such as X (Twitter), TikTok, YouTube, and online review platforms, while also incorporating manual validation techniques and comparative sentiment analysis methods to improve robustness and comprehensiveness.

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