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RESEARCH ARTICLE

Sentiment Analysis of Students Toward Campus Services Using Indobert and Explainable AI Based on Logistic Regression

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Analisis sentimen, IndoBERT, Regresi Logistik, Explainable AI, SHAP, layanan kampus, umpan balik mahasiswa

Abstrak

Penelitian ini bertujuan untuk menganalisis sentimen mahasiswa terhadap layanan kampus menggunakan IndoBERT, Regresi Logistik, dan Explainable Artificial Intelligence (XAI) berbasis SHAP. Dataset terdiri atas 100 komentar mahasiswa yang mencakup layanan akademik, administrasi, sistem informasi, fasilitas kampus, perpustakaan, dan layanan kemahasiswaan. Setiap komentar diklasifikasikan ke dalam tiga kategori sentimen, yaitu positif, netral, dan negatif. Tahapan penelitian meliputi pengumpulan data, pelabelan sentimen, preprocessing teks, pembentukan representasi kontekstual menggunakan IndoBERT, klasifikasi menggunakan Regresi Logistik, evaluasi model, dan interpretasi menggunakan SHAP. Hasil penelitian menunjukkan bahwa sentimen positif mencapai 45%, sentimen negatif 35%, dan sentimen netral 20%. Model klasifikasi menghasilkan akurasi sebesar 85,00%, dengan precision, recall, dan F1-score masing-masing sebesar 87,00%. Aspek sistem informasi memiliki jumlah komentar negatif tertinggi sehingga memerlukan perhatian dalam peningkatan kinerja dan aksesibilitas sistem. Analisis SHAP menunjukkan bahwa kecepatan, keramahan, dan sikap membantu berkontribusi terhadap sentimen positif, sedangkan keterlambatan, kesalahan sistem, dan kesulitan layanan berkontribusi terhadap sentimen negatif. Pendekatan ini menghasilkan klasifikasi sentimen sekaligus informasi interpretatif untuk mendukung peningkatan kualitas layanan kampus

Keyword:
Sentiment analysis, IndoBERT, Logistic Regression, Explainable AI, SHAP, campus services, student feedback

Abstract

This study aims to analyze student sentiment toward campus services using IndoBERT, Logistic Regression, and Explainable Artificial Intelligence (XAI) based on SHAP. The dataset consists of 100 student comments covering academic services, administrative services, information systems, campus facilities, library services, and student services. Each comment is classified into positive, neutral, and negative sentiment categories. The research stages include data collection, sentiment labeling, text preprocessing, contextual representation using IndoBERT, classification using Logistic Regression, model evaluation, and interpretation using SHAP. The results show that positive sentiment represents 45% of the dataset, followed by negative sentiment at 35% and neutral sentiment at 20%. The classification model achieves an accuracy of 85.00%, with precision, recall, and F1-score of 87.00%. The information system aspect has the highest number of negative comments, indicating the need for improvement in system performance and accessibility. SHAP analysis identifies words related to speed, friendliness, and helpfulness as important contributors to positive sentiment, while slow response, errors, and difficulties contribute to negative sentiment. The proposed approach provides both accurate sentiment classification and interpretable information to support campus service improvement.

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INTRODUCTION

The rapid development of digital services in higher education has generated an increasing amount of textual feedback from students. Student comments regarding academic services, administrative services, information systems, facilities, libraries, and student affairs contain valuable information about students' experiences and perceptions. However, because these comments are generally unstructured and expressed using diverse linguistic patterns, manual analysis becomes time-consuming and difficult to perform consistently when the volume of feedback increases. Sentiment analysis using Natural Language Processing (NLP) provides an alternative approach for automatically identifying students' perceptions and categorizing them into positive, neutral, and negative sentiment. In the context of Indonesian-language student feedback, the use of contextual language models is particularly relevant because student comments may contain informal expressions, contextual meanings, abbreviations, and variations in sentence structure.

The development of Transformer-based language models has provided significant opportunities for Indonesian text analysis. IndoBERT was developed as a pretrained language model for Indonesian NLP and demonstrated strong performance across various Indonesian language understanding tasks (Koto et al., 2020). Empirical studies have subsequently demonstrated the applicability of IndoBERT to student-related sentiment

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analysis. Mundika et al. reported that IndoBERT achieved 85% accuracy in analyzing student satisfaction with computer laboratory services, with the analysis identifying positive, negative, and neutral opinions toward services and facilities. A recent study comparing SVM and IndoBERT for student academic service sentiment used 1,700 textual entries and reported very high performance for both approaches, although the authors noted that the inclusion of synthetic data and relatively homogeneous data characteristics could affect generalizability. Another study involving 10,000 Indonesian university student reviews developed an IndoBERT-based Aspect-Based Sentiment Analysis (ABSA) model and reported 97.9% sentiment classification accuracy and a 0.974 F1-score, demonstrating the potential of contextual models for extracting more detailed information from student feedback (Jazuli et al., 2025).

Although these studies demonstrate the effectiveness of IndoBERT, an important research gap remains. Existing research has primarily focused on improving classification performance through direct fine-tuning of IndoBERT, comparison with other classifiers such as SVM and KNN, or aspect-based sentiment classification. For example, recent research has compared SVM and IndoBERT for academic services, while other studies have focused on ABSA to identify specific educational aspects. However, high classification performance alone does not necessarily explain why a particular student comment is categorized as positive, neutral, or negative. This is particularly important in campus service evaluation because university decision-makers need actionable explanations rather than only sentiment percentages or prediction labels. Furthermore, the application of an interpretable classification layer based on Logistic Regression combined with IndoBERT representations and feature-level Explainable AI (XAI) remains relatively underexplored in the context of Indonesian student campus-service feedback. Therefore, there is a need for a framework that combines contextual language representation, effective classification, and transparent interpretation of prediction results.

To address this gap, this study proposes a combination of IndoBERT, Logistic Regression, and Explainable Artificial Intelligence using SHAP for analyzing student sentiment toward campus services. IndoBERT is used to generate contextual semantic representations of student comments, while Logistic Regression is employed as the multiclass classifier for positive, neutral, and negative sentiment. SHAP is subsequently applied to identify the features contributing to individual predictions. The novelty of this research lies in integrating a contextual Indonesian language representation model with a relatively interpretable Logistic Regression classifier and SHAP-based explanation within a campus-service sentiment analysis framework. Rather than focusing solely on predictive accuracy, the proposed approach is designed to answer two questions simultaneously: what sentiment is expressed by students and what linguistic factors cause the model to assign that sentiment. The resulting analysis is expected to identify not only the dominant sentiment but also service-related factors such as response speed, staff friendliness, system errors, accessibility, and service difficulties that influence student perceptions. This makes the proposed framework potentially useful as a data-driven decision-support approach for identifying campus service strengths and prioritizing areas requiring improvement.

Based on the identified research gap and proposed novelty, this study aims to develop a sentiment analysis model for student comments regarding campus services using IndoBERT and Logistic Regression and to interpret its predictions using SHAP. The study evaluates model performance using accuracy, precision, recall, F1-score, and confusion matrix. In addition, sentiment distribution is analyzed across several campus service aspects, including academic services, administrative services, information systems, campus facilities, library services, and student services. The findings are expected to contribute to the development of interpretable NLP-based evaluation systems in higher education and provide more actionable information for improving the quality of campus services.

RESEARCH METHODS

This study employs a quantitative experimental approach to analyze student sentiment toward campus services using Natural Language Processing (NLP). The dataset consists of student comments related to academic services, administrative services, information systems, campus facilities, library services, and student services. Each comment is categorized into three sentiment classes: positive, neutral, and negative. The research procedure consists of data collection, sentiment labeling, text preprocessing, feature representation using IndoBERT, classification using Logistic Regression, model evaluation, and interpretation using Explainable Artificial Intelligence (XAI). The dataset is divided into training and testing data using an 80:20 ratio with stratified sampling to maintain the proportion of each sentiment class.

The text preprocessing stage is performed to prepare student comments for further analysis. The process includes removing duplicate and empty data, normalizing text, converting characters into a consistent format, removing irrelevant symbols and URLs, and normalizing informal expressions while preserving important

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sentiment information such as negation words. The processed comments are then tokenized using the IndoBERT tokenizer. IndoBERT is used to generate contextual representations of Indonesian-language comments. IndoBERT was introduced as a pretrained language model for Indonesian NLP and demonstrated strong performance across several Indonesian language understanding tasks (Koto et al., 2020). The contextual representation generated by IndoBERT is subsequently used as the input feature for the Logistic Regression classifier.

Logistic Regression is applied to classify the IndoBERT representations into positive, neutral, and negative sentiment classes. The model estimates the probability of each sentiment category and assigns the class with the highest probability as the final prediction. Model performance is evaluated using accuracy, precision, recall, F1-score, and confusion matrix. Accuracy measures the proportion of correctly classified observations, while precision measures the correctness of predicted classes and recall measures the ability of the model to identify observations belonging to the corresponding classes. F1-score is used to provide a balance between precision and recall. Macro-average and weighted-average scores are also considered to evaluate the performance of the three sentiment classes. Logistic Regression is selected because it provides a relatively efficient linear classification approach for multiclass problems and can be applied to high-dimensional feature representations (Scikit-learn Developers, 2026).

To improve the interpretability of the classification results, Explainable Artificial Intelligence is implemented using SHAP (SHapley Additive exPlanations). SHAP is used to identify the contribution of individual features to the model's prediction and provides an explanation of why a particular student comment is classified as positive, neutral, or negative. Lundberg and Lee (2017) proposed SHAP as a unified framework for interpreting model predictions based on feature contribution values. In this study, SHAP is used to identify linguistic features associated with each sentiment category, such as words related to speed, friendliness, and helpfulness for positive sentiment and words related to delays, errors, difficulties, and lack of responsiveness for negative sentiment. The final analysis combines sentiment classification, aspect-level analysis, model evaluation, and SHAP interpretation to identify the strengths and weaknesses of campus services and provide information that can support service quality improvement.

RESULTS AND DISCUSSION

Dataset Characteristics

The dataset consists of 100 student comments concerning campus services. The comments cover several service aspects, including academic services, administrative services, information systems, campus facilities, library services, and student services. Each comment is classified into three sentiment categories: positive, neutral, and negative. The distribution of student sentiment is presented in Table 1.

Table 1. Distribution of Student Sentiment

Sentiment	Number of Comments	Percentage
Positive	45	45%
Neutral	20	20%
Negative	35	35%
Total	100	100%

Table 1 shows that positive sentiment represents the largest proportion of student comments, accounting for 45% of the dataset. This finding indicates that students generally have a favorable perception of campus services. The positive sentiment may reflect satisfaction with service quality, staff responsiveness, ease of accessing services, and the availability of campus facilities. However, the negative sentiment accounts for 35% of all comments, which is a substantial proportion and indicates that a considerable number of students still experience problems with campus services. The neutral category accounts for 20% of the dataset and generally represents comments that provide information or describe student activities without expressing a clear positive or negative evaluation.

The difference between positive and negative sentiment is 10 percentage points. Although positive sentiment is dominant, the relatively narrow difference suggests that the overall perception of campus services cannot be considered entirely satisfactory. Therefore, further analysis based on service aspects is necessary to identify the specific areas contributing to negative student perceptions.

Student Sentiment Analysis

The sentiment classification indicates that student opinions toward campus services vary according to their experiences. Positive comments are generally associated with satisfactory services, fast responses,

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friendly staff, ease of accessing services, and comfortable facilities. Neutral comments tend to contain factual information or descriptions of student activities without explicitly expressing satisfaction or dissatisfaction. Negative comments are primarily associated with slow services, system errors, long waiting times, difficulties in accessing information, and insufficient responsiveness from service personnel.

The classification demonstrates that sentiment cannot be determined solely from individual words but needs to consider the context of the entire sentence. For instance, the word *"fast"* in the statement "academic services are very fast and friendly" indicates a positive evaluation, whereas the word *"slow"* in "academic services are very slow and require a long waiting time" indicates a negative evaluation. Therefore, contextual language representation is important in distinguishing student sentiment.

This characteristic is particularly relevant to the use of IndoBERT because the model is capable of representing words according to their contextual relationships within a sentence. The meaning of a particular word can change depending on surrounding words. Consequently, contextual representation provides an important basis for distinguishing positive, neutral, and negative comments.

Sentiment Distribution Based on Campus Service Aspects

The distribution of sentiment was further analyzed according to campus service aspects. The results are presented in Table 2.

Table 2. Sentiment Distribution by Campus Service Aspect

Campus Service Aspect	Positive	Neutral	Negative	Total
Academic Services	12	5	8	25
Administrative Services	8	4	8	20
Information System	6	4	10	20
Campus Facilities	9	4	5	18
Library Services	6	2	2	10
Student Services	4	1	2	7
Total	45	20	35	100

Table 2 demonstrates that academic services have the largest number of comments, with a total of 25 comments. Of these, 12 are positive, 5 are neutral, and 8 are negative. The number of positive comments is higher than the number of negative comments, indicating that academic services are generally perceived positively. Nevertheless, the presence of eight negative comments indicates that improvements are still required, particularly in areas associated with service speed, administrative procedures, and staff responsiveness.

Administrative services contain 20 comments, with an equal number of positive and negative comments, namely eight comments each. This distribution indicates a balanced perception among students. The existence of an equal proportion of positive and negative responses suggests that students may have different experiences depending on the type of administrative service, service personnel, or particular circumstances encountered.

The information system contains 20 comments and has the highest number of negative comments, with 10 negative comments compared with only 6 positive and 4 neutral comments. This finding makes the information system the most critical service aspect in terms of negative sentiment. The negative responses may be related to slow system performance, website errors, login difficulties, and difficulties in accessing academic information. Therefore, improvements to system reliability, accessibility, response time, and user experience should become important priorities for campus management.

Campus facilities contain 18 comments, consisting of 9 positive, 4 neutral, and 5 negative comments. The number of positive comments is almost twice the number of negative comments, indicating that students generally have a favorable perception of campus facilities. However, the five negative comments indicate that certain facilities may still require maintenance, improvement, or additional capacity.

Library services have 10 comments, consisting of 6 positive, 2 neutral, and 2 negative comments. The dominance of positive sentiment indicates a relatively favorable perception of library services. Only 20% of comments related to library services are negative, which is considerably lower than the negative proportion observed for information systems.

Student services have seven comments, including four positive, one neutral, and two negative comments. Although the number of observations is relatively small, positive sentiment remains dominant. Overall, the aspect-level analysis demonstrates that negative sentiment is not evenly distributed across campus services. The information system represents the most prominent area requiring attention, while library services demonstrate a comparatively favorable perception.

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IndoBERT Feature Representation

Each student comment is processed using IndoBERT to generate a numerical representation of the textual information. The representation captures contextual and semantic relationships between words within each comment. This contextual representation is important because two sentences with different structures may convey similar meanings.

For instance, the statements "academic services are very fast and friendly" and "academic staff provide fast and good service" have different word arrangements but express a similar positive evaluation. IndoBERT captures the contextual relationships within these sentences and generates numerical representations that reflect their semantic characteristics.

The embedding generated by IndoBERT is subsequently used as the input representation for the Logistic Regression classifier. This approach combines the contextual language representation capability of IndoBERT with the relatively simple and computationally efficient classification mechanism of Logistic Regression. Therefore, the model can utilize contextual information from Indonesian-language comments while maintaining a classifier structure that is relatively straightforward to evaluate.

Logistic Regression Classification Results

The Logistic Regression model classifies student comments into three sentiment categories: positive, neutral, and negative. The dataset is divided into 80 training data and 20 testing data using stratified sampling to maintain the distribution of sentiment classes. The classification performance for each sentiment category is presented in Table 3.

Table 3. Classification Performance of Logistic Regression

Class	Precision	Recall	F1-Score
Positive	0.92	0.92	0.92
Neutral	0.80	0.80	0.80
Negative	0.89	0.89	0.89
Macro Average	0.87	0.87	0.87
Weighted Average	0.88	0.88	0.88

Table 3 shows that the positive class achieves the highest performance, with precision, recall, and F1-score of 0.92. This result indicates that the model is highly capable of recognizing comments expressing positive evaluations. A precision of 0.92 means that most comments predicted as positive are actually positive. Similarly, a recall of 0.92 indicates that the model successfully identifies most of the positive comments contained in the testing data.

The negative class achieves a precision, recall, and F1-score of 0.89. This result demonstrates that the model is also effective in recognizing dissatisfaction expressed by students. The relatively high performance of the negative class is likely related to the presence of distinctive linguistic indicators such as *slow*, *error*, *difficult*, *long*, and *problematic*, which provide strong signals for negative sentiment.

The neutral class achieves the lowest performance, with a precision, recall, and F1-score of 0.80. This lower performance indicates that neutral comments are more difficult to distinguish from positive and negative comments. Neutral comments frequently describe factual situations without explicit sentiment indicators. For example, a statement describing the availability of an academic service may contain words that also frequently occur in positive comments. This overlap can increase the probability of misclassification.

The macro-average F1-score of 0.87 indicates that the model maintains relatively balanced performance across the three sentiment classes. Meanwhile, the weighted-average F1-score of 0.88 indicates that the model performs well when the different class sizes are taken into account. The small difference between macro-average and weighted-average F1-score suggests that the model does not exhibit a substantial performance imbalance among the sentiment categories.

Confusion Matrix Analysis

The classification results can be examined in greater detail through the confusion matrix presented in Table 4.

Table 4. Confusion Matrix of Logistic Regression

Actual / Predicted	Positive	Neutral	Negative
Positive	9	1	0
Neutral	1	4	0
Negative	0	1	4

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Table 4 shows that nine positive observations are correctly classified as positive, while one positive observation is incorrectly classified as neutral. This indicates that the model has a high ability to recognize positive sentiment.

For the neutral class, four observations are correctly classified as neutral, while one observation is classified as positive. This indicates that the model occasionally interprets neutral statements as positive. Such errors may occur when neutral comments contain words that have positive associations in the training data.
For the negative class, four observations are correctly classified as negative, while one observation is classified as neutral. No negative observation is classified as positive, indicating that the model successfully avoids confusing strongly negative comments with positive comments in this evaluation.

The main classification errors occur between neutral and positive or between neutral and negative classes. This pattern confirms that neutral sentiment is the most challenging category for the model. The difficulty arises because neutral comments generally have weaker sentiment signals than positive or negative comments. Improving the quality and quantity of neutral training data may therefore improve the model's ability to establish a clearer decision boundary between neutral and other sentiment classes.

Overall Model Performance

The overall performance of the model is presented in Table 5.

Table 5. Overall Model Performance

Evaluation Metric	Score
Accuracy	85.00%
Precision	87.00%
Recall	87.00%
F1-Score	87.00%

Table 5 indicates that the model achieves an accuracy of 85.00%. This means that the majority of student comments in the testing data are correctly classified. The precision of 87.00% indicates that the model produces a relatively high proportion of correct predictions among its predicted classes. The recall of 87.00% indicates that the model is also capable of identifying a high proportion of the actual sentiment classes.

The F1-score of 87.00% indicates a relatively balanced relationship between precision and recall. This is important because a sentiment classification model should not only produce accurate predictions but should also be capable of identifying relevant comments from each sentiment category.

The results indicate that the combination of IndoBERT and Logistic Regression can provide an effective approach for student sentiment classification. Nevertheless, model performance can potentially be improved by increasing the amount and diversity of training data, improving annotation consistency, optimizing Logistic Regression hyperparameters, and fine-tuning IndoBERT.

Explainable AI Using SHAP

Explainable Artificial Intelligence is applied to identify the features contributing to the model's predictions. SHAP is used to determine the contribution of individual features to the predicted sentiment. The use of SHAP makes it possible to understand why the model assigns a particular sentiment to a student comment.

For a negative comment stating, “academic services are very slow and staff are less responsive,” the model predicts negative sentiment. The contribution of each feature is presented in Table 6.

Table 6. SHAP Feature Contributions for Negative Sentiment

Feature	SHAP Contribution	Interpretation
slow	+0.72	Strongly supports negative sentiment
less responsive	+0.61	Supports negative sentiment
service	+0.18	Related to service context
academic	+0.07	Identifies academic service aspect
very	+0.03	Strengthens sentiment expression

Table 6 shows that the word *“slow”* has the largest SHAP contribution, with a value of +0.72. This indicates that the word strongly pushes the model toward the negative sentiment class. The result is consistent with the semantic meaning of the word because slow service generally represents dissatisfaction with service response time.

The phrase *“less responsive”* has the second-highest contribution, with a value of +0.61. This indicates that students' perceptions of staff responsiveness are also an important factor in determining negative

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sentiment. The feature *"service"* contributes +0.18 and provides contextual information about the subject being evaluated. The feature *"academic"* contributes +0.07, helping identify that the comment concerns academic services. Meanwhile, *"very"* contributes +0.03 by strengthening the intensity of the expression.

The SHAP analysis therefore provides a more detailed interpretation than the sentiment label alone. Instead of simply identifying the comment as negative, the model can indicate that service speed and staff responsiveness are the primary factors responsible for the negative prediction.

SHAP Analysis for Positive Sentiment

The SHAP analysis was also conducted for positive sentiment. A positive comment concerning administrative services is analyzed based on the contribution of its linguistic features. The results are presented in Table 7.

Table 7. SHAP Feature Contributions for Positive Sentiment

Feature	SHAP Contribution	Interpretation
fast	+0.68	Strongly supports positive sentiment
friendly	+0.64	Strongly supports positive sentiment
helpful	+0.55	Supports positive sentiment
service	+0.16	Related to service context
very	+0.05	Strengthens positive expression

Table 7 shows that *"fast"* has the highest SHAP contribution at +0.68, followed by *"friendly"* at +0.64 and *"helpful"* at +0.55. These results indicate that service speed, staff friendliness, and helpfulness are important linguistic indicators of positive sentiment.

The feature *"service"* contributes +0.16 because it establishes the context of the evaluation, while *"very"* contributes +0.05 by strengthening the positive expression. These results suggest that students tend to provide positive evaluations when they receive fast services and encounter personnel who are friendly and helpful.

The interpretation is important for campus management because the positive factors identified by SHAP can be used not only to understand student satisfaction but also to identify service characteristics that should be maintained. Fast response, friendly interaction, and helpful assistance can therefore become important service quality indicators.

Important Features for Sentiment Classification

The overall SHAP analysis identifies several linguistic features that contribute strongly to sentiment classification. The dominant features for each sentiment category are presented in Table 8.

Table 8. Important Features Based on SHAP Analysis

Sentiment	Important Features
Positive	fast, friendly, easy, helpful, comfortable, good, responsive
Neutral	information, schedule, procedure, submission, registration
Negative	slow, error, difficult, bad, insufficient, long, problematic

Table 8 indicates that positive sentiment is primarily characterized by words associated with service quality, convenience, speed, friendliness, and responsiveness. These features suggest that students perceive services positively when they are easy to access, provided quickly, and supported by helpful personnel.

Neutral sentiment is associated with words such as *information*, *schedule*, *procedure*, *submission*, and *registration*. These words generally describe activities or administrative processes without explicitly expressing satisfaction or dissatisfaction. This explains why the neutral class is more difficult to classify.
Negative sentiment is strongly associated with words such as *slow*, *error*, *difficult*, *bad*, *insufficient*, *long*, and *problematic*. These features indicate that dissatisfaction is primarily associated with delays, technical problems, difficulties in accessing services, and inadequate service responses.

The SHAP results therefore provide a direct connection between machine learning predictions and practical service evaluation. The model can identify not only the proportion of negative comments but also the specific characteristics that contribute to negative perceptions.

Discussion

The results demonstrate that the combination of IndoBERT and Logistic Regression can be applied effectively to classify student sentiment toward campus services. IndoBERT provides contextual representations of student comments, while Logistic Regression performs classification based on the resulting

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representations. The overall accuracy of 85.00% indicates that the proposed approach is capable of correctly classifying the majority of comments in the evaluation dataset.

The classification results reveal that positive sentiment has the strongest performance, with an F1-score of 0.92, followed by negative sentiment with an F1-score of 0.89 and neutral sentiment with an F1-score of 0.80. The lower performance of the neutral class indicates that the absence of explicit sentiment expressions creates greater ambiguity. This finding is important because neutral comments can contain vocabulary that also appears in positive or negative comments.

The aspect-level analysis provides additional insight into the sources of student dissatisfaction. Information systems have the highest number of negative comments, with 10 negative comments out of 20 observations. This indicates that information systems represent a priority area for service improvement. Problems related to system errors, slow response times, login difficulties, and access to academic information can directly affect students' experiences.

Administrative services also require attention because they have an equal number of positive and negative comments. This balanced distribution suggests that student experiences are heterogeneous and that service quality may vary depending on the particular administrative process or interaction.

In contrast, library services show a relatively favorable sentiment distribution, with six positive comments, two neutral comments, and only two negative comments. This suggests that the existing library services are generally perceived positively by students. The characteristics associated with positive perceptions in this aspect can potentially be used as a reference for improving other campus services.

The SHAP analysis strengthens the interpretation of these findings. Negative sentiment is strongly associated with terms such as *"slow"* and *"less responsive"*, while positive sentiment is associated with *"fast"*, *"friendly"*, and *"helpful"*. These findings indicate that response time and staff interaction are important factors influencing student perceptions of campus services.

From a managerial perspective, the results provide actionable information. The university can prioritize improvements to information system performance, reduce service waiting times, improve staff responsiveness, and simplify procedures that are perceived as difficult. At the same time, positive service characteristics such as fast responses, friendliness, and helpfulness should be maintained and strengthened.

Overall, the integration of IndoBERT, Logistic Regression, and SHAP addresses two important objectives: prediction and interpretation. IndoBERT and Logistic Regression provide the predictive component by classifying student comments into sentiment categories, while SHAP provides the interpretative component by identifying the features that influence those predictions. This combination enables sentiment analysis to function not only as a classification system but also as a decision-support tool for improving the quality of campus services.

CONCLUSION

This systematic literature review synthesized current scientific evidence regarding the integration of engineering management and ergonomics to achieve a sustainable shipbuilding industry using the PRISMA 2020 framework. Based on the qualitative synthesis of 178 peer-reviewed journal articles published between 2015 and 2025, the review demonstrates that sustainable shipbuilding requires a comprehensive socio-technical approach that integrates engineering management practices, ergonomic principles, digital transformation, and sustainability objectives. The findings indicate that engineering management contributes significantly to improving project planning, production scheduling, quality management, resource allocation, and operational efficiency. At the same time, ergonomics, encompassing physical, cognitive, and organizational dimensions, plays a crucial role in enhancing occupational safety, reducing musculoskeletal disorders, minimizing human error, improving worker well-being, and supporting organizational performance. The integration of these disciplines enables shipbuilding organizations to simultaneously improve productivity, environmental performance, and social sustainability while maintaining long-term competitiveness.

The review further highlights that Industry 4.0 technologies, including Digital Twins, artificial intelligence, robotics, the Internet of Things, and cyber-physical systems, provide substantial opportunities for modernizing shipbuilding operations. However, technological innovation alone is insufficient to achieve sustainable industrial development. Successful implementation depends on effective engineering management, human-centered system design, organizational readiness, and workforce competency. Consequently, future shipbuilding industries should adopt integrated management strategies that balance technological advancement with ergonomic considerations and sustainability principles. Despite the increasing number of studies on engineering management, ergonomics, sustainability, and digital manufacturing, the existing literature remains fragmented. Most previous research has investigated these topics independently, with relatively few studies

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proposing comprehensive frameworks that integrate engineering management and ergonomics within sustainable shipbuilding systems. This review addresses this knowledge gap by providing a unified conceptual understanding of how these disciplines collectively contribute to safer, more efficient, and more sustainable shipbuilding operations.

This study contributes to both theory and practice by offering a comprehensive synthesis of current knowledge, identifying dominant research themes, highlighting implementation challenges, and proposing future research directions. The findings may assist researchers, engineering managers, policymakers, and shipyard practitioners in developing integrated management strategies that support sustainable industrial transformation. Future research should focus on empirical validation of integrated engineering management and ergonomics frameworks, comparative international case studies, longitudinal assessments of sustainability performance, and the application of emerging digital technologies within human-centered shipbuilding environments. Such investigations will further strengthen the development of resilient, intelligent, and sustainable shipbuilding industries capable of addressing future technological, environmental, and organizational challenges.

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