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Sentiment Analysis And UTAUT2 Classification On Maxim Application User Reviews Using IndoBERT And Zero-Shot

Hilal Hindi Saputra[1], Cendra Devayana Putra[2], I Kadek Dwi Nuryana[3], Monica Cinthya[4]

[1,2,3,4]*Universitas Negeri Surabaya, Surabaya, Indonesia*

hilal.21067@mhs.unesa.ac.id, putracendra@unesa.ac.id

dwinuryana@unesa.ac.id, monicacinthya@unesa.ac.id

ABSTRACT

The rapid growth of ride-hailing services has intensified competition, making user feedback on digital platforms a critical asset for service improvement. This study addresses the challenge of managing and extracting actionable insights from large volumes of unstructured user reviews on the Google Play Store for the Maxim application. To overcome this, a comprehensive text-mining framework is proposed, integrating sentiment analysis and technology acceptance modeling. A dataset of 2.000 Indonesian-language user reviews from July to September 2025 was retrieved via web scraping. Data preprocessing was executed using case folding, filtering, and normalization. Subsequently, sentiment classification was performed using the IndoBERT model, while the mapping of user text to the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework was automated using a Zero-Shot Classification approach. Finally, Structural Equation Modeling–Partial Least Squares (SEM-PLS) via SmartPLS 4.0 was utilized to test the structural hypotheses. The analytical findings reveal that negative sentiments slightly dominate the dataset (48.05%), heavily driven by system stability and sudden fare adjustments. Furthermore, the structural model proves that behavioral intention, effort expectancy, facilitating conditions, habit, performance expectancy, price value, and social influence exert positive and significant effects on adoption, whereas hedonic motivation exhibits no significant influence.

Keywords: IndoBERT, Maxim Application, Sentiment Analysis, SEM-PLS, UTAUT2, Zero-Shot Classification

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Corresponding Author
Hilal Hindi Saputra
Universitas Negeri Surabaya, Surabaya, Indonesia
Hilal.21067@mhs.unesa.ac.id

1. INTRODUCTION

The development of digital technology in the modern era has brought significant changes to various sectors of life, including the transportation sector in Indonesia [1], [2]. This transformation is characterized by the presence of application-based transportation services that offer convenience, speed, and efficiency in public mobility. Prior to the adoption of digital technology, users had to search for conventional transportation, which required greater time and effort [2]. However, with the increasing penetration of the internet and mobile device usage [3], online transportation services have now become the primary solution for the community's

daily mobility needs. This condition indicates that information technology plays a crucial role in shaping user behavior and preferences toward modern transportation services.

Online transportation services are not limited to passenger delivery but also encompass goods and food delivery. One of the rapidly growing applications in Indonesia is Maxim, which offers transportation services with a competitive pricing concept and an expansive coverage area [4]. In an increasingly tight online transportation industry competition, user feedback becomes a crucial element in evaluating service quality and application success. The Google Play Store provides review and star-rating features that allow users to openly convey their experiences, satisfaction, or complaints. Every day, thousands of new reviews are generated, forming a massive collection of data rich in information, yet difficult to analyze manually without an automated approach [5].

Text-based user reviews are subjective, unstructured, and frequently contain more than one perception within a single statement. Therefore, a *Natural Language Processing* (NLP) approach is required to systematically process such data [6]. Sentiment analysis is utilized to identify the tendency of user opinions, whether they are positive, negative, or neutral [7]. Previous research demonstrates that the IndoBERT model is capable of understanding the context of the Indonesian language well and yields high performance in sentiment classification compared to conventional methods [8]. Through sentiment analysis, application developers can obtain a general overview regarding the level of satisfaction and the problems most frequently experienced by users.

Although sentiment analysis can describe the tendency of user opinions, this approach is insufficient to explain the factors influencing technology acceptance and usage in a deeper manner. To achieve this, a theoretical framework is necessary to explain the relationship between user perception, behavioral intention, and actual usage behavior. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model offers a comprehensive framework with seven core constructs: *performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value,* and *habit* [9]. However, the majority of UTAUT2 studies still rely on questionnaire data [10], thus underrepresenting the spontaneous opinions of users on a large scale.

Addressing these challenges, this study integrates sentiment analysis using IndoBERT with a *Zero-Shot Classification* approach to classify UTAUT2 constructs directly from the text of Maxim application user reviews. The zero-shot approach enables the classification process to be performed without manual labeling, making it more efficient and adaptive to large datasets. Furthermore, the classification results are utilized to examine the relationships between UTAUT2 constructs using *the Partial Least Square–Structural Equation Modeling* (PLS-SEM) method [11]. This research is expected to provide practical contributions for Maxim application developers as well as theoretical contributions to the advancement of technology acceptance analysis based on Indonesian-language user reviews.

2. METHODS

The research method in this study is utilized to explain the stages conducted in analyzing sentiment and classifying the UTAUT2 dimensions of Maxim application user reviews. Generally, this research method encompasses the adopted research approach, data sources, and data collection techniques, as well as data analysis techniques which include data preprocessing, sentiment analysis, *zero-shot* labeling of UTAUT2 dimensions, and the analysis of relationships between variables using the Structural Equation Modeling–Partial Least

Square (SEM-PLS) method. This sequence of phases is structured systematically to obtain research results that are objective, measurable, and aligned with the research objectives.

2.1 Research Approach

The research approach adopted in this study is a quantitative approach, utilized to objectively measure the relationships between variables and test predetermined hypotheses based on numerical data. According to Sugiyono, a quantitative research method is founded on the philosophy of positivism, used to investigate specific populations or samples, gather data through research instruments, and perform quantitative or statistical data analysis to test established hypotheses [10]. This approach was selected due to its alignment with the characteristics of the research data, which consist of sentiment classification outcomes and UTAUT2 dimensions that are subsequently analyzed statistically using the *Structural Equation Modeling–Partial Least Square* (SEM-PLS) method [11].

2.2 Data Sources and Collection

The data source utilized in this study comprises secondary data obtained from Maxim application user reviews on the Google Play Store [4]. The review data were gathered using a *web scraping* technique, leveraging the Python library *google-play-scraper* for the collection period from July 2025 to September 2025, which extracted review text, rating scores, and review dates [5]. The collected data consist of Indonesian-language reviews, with the retrieval period adjusted to match information availability and completeness [3]. A total of 2,000 review entries were used in this study, determined based on analysis requirements while considering computational efficiency and data distribution consistency. The retrieved reviews were subsequently filtered to ensure the data were relevant, non-duplicated, and contained valid text content. These selected data were then employed as the primary input for the sentiment analysis, the labeling of UTAUT2 dimensions, and the evaluation of relationships between variables within the research model.

2.3 Data Analysis Techniques

2.3.1 Data Preprocessing

The data preprocessing stage is conducted to clean and prepare the text data so it can be effectively processed by the analytical models. This preprocessing phase encompasses *case folding* to convert all text into lowercase, the removal of punctuation, numbers, symbols, and emojis, as well as the elimination of *stopwords*. Additionally, word normalization is performed to reduce lexical variations of words that possess identical meanings [7]. This stage fundamentally aims to enhance data quality and optimize the performance of the subsequent analysis models utilized in the study [6].

Table 1. Example of Data Processing Results

Raw_text	**Preprocesed_text**
ojek online terpercaya dan sangat nyaman	ojek online terpercaya dan sangat nyaman
pake Maxim enak banget coy ril🔥☆☆☆☆☆	pake maxim enak banget coy ril

2.3.2 Sentiment Analysis

Sentiment analysis in this study aims to identify the tendencies of user opinions toward the Maxim application based on the reviews provided on the

Google Play Store [4], [5]. Each review is classified into three sentiment categories: positive, negative, and neutral, which serve to represent user satisfaction, dissatisfaction, or informative opinions regarding the application services, thereby providing a comprehensive overview of user perception [1]. This sentiment analysis process is executed utilizing the IndoBERT model, a *pre-trained language model* based on the BERT architecture specifically optimized for the Indonesian language [8]. IndoBERT possesses the capability to understand sentence contexts bidirectionally, enabling it to capture word meanings based on the interrelationships of words within a sentence. This model is highly suitable for processing user reviews that are generally informal, varied, and unstructured. Each preprocessed review is evaluated by the model to generate probabilities for each sentiment class, and the final sentiment label is subsequently determined based on the highest probability value. The resulting sentiment labels for each user review then serve as the foundational baseline for the subsequent analytical stages, which involve the labeling of UTAUT2 dimensions and the evaluation of structural relationships using SEM-PLS. Consequently, sentiment analysis does not merely depict user opinion tendencies but also plays a critical role in constructing the technology acceptance analysis model based on Maxim application user reviews.

Table 2. Example of Sentiment Analysis Results

Preprocesed_text	**Sentiment_label**	**Confidence score**
ojek online terpercaya dan sangat nyaman	Positif	0.9988619089126587
pake maxim enak banget coy ril	Positif	0.9990676045417786

2.3.3 UTAUT2 Construct Labelling

The labeling of UTAUT2 constructs in this study is executed using a *Zero-Shot Classification* approach, a classification method that enables the model to categorize text into specific groups without requiring manually labeled training data. This approach was selected due to its capability to overcome the limitations of labeled data and its higher efficiency in processing large amounts of user review data [6]. By utilizing the *zero-shot* approach, the model can identify the semantic relationships between the review text and the description of each UTAUT2 construct based on semantic alignment, thereby allowing the labeling process to be performed automatically and objectively. Each user review in this research is permitted to have more than one construct label; hence, a *multi-label* classification mechanism is applied. This reflects the real-world condition where a single user review frequently contains more than one evaluative aspect regarding the application. The UTAUT2 constructs utilized in the labeling process encompass *performance expectancy*, *effort expectancy*, *social influence*, *facilitating conditions*, *hedonic motivation*, *price value*, and *habit* [9]. The outcomes of this UTAUT2 construct labeling are subsequently utilized as the foundation for analyzing the relationships between constructs using the SEM-PLS method to test the research hypotheses.

Table 3. Example of UTAUT2 Dimension Labelling Results

Preprocesed_text	Sentiment_label	Label UTAUT2
ojek online terpercaya dan sangat nyaman	Positif	{'label': 'Facilitating Conditions', 'score': 0.9832521080970764}, {'label': 'Use Behavior', 'score': 0.8413101434707642}, {'label': 'Price Value', 'score': 0.7807475924491882}, {'label': 'Behavioral Intention', 'score': 0.7590396404266357}
pake maxim enak banget coy ril	Positif	{'label': 'Effort Expectancy', 'score': 0.9804217219352722}, {'label': 'Performance Expectancy', 'score': 0.9612669944763184}, {'label': 'Use Behavior', 'score': 0.9448720812797546}, {'label': 'Facilitating Conditions', 'score': 0.8788635730743408}, {'label': 'Hedonic Motivation', 'score': 0.7885591983795166}, {'label': 'Habit', 'score': 0.7832486033439636}, {'label': 'Behavioral Intention', 'score': 0.7466773390769958}

2.3.4 Data Analysis Using SEM-PLS

The final stage of data analysis is executed utilizing the *Structural Equation Modeling–Partial Least Square* (SEM-PLS) method with the assistance of SmartPLS 4.0 software [11]. The SEM-PLS method is employed to evaluate the relationships between constructs within the UTAUT2 model and to determine whether the research hypotheses are accepted or rejected based on *t-statistic* and *p-value* metrics [10]. The utilization of SmartPLS 4.0 is deemed appropriate for this study due to its capability to handle complex models and non-normally distributed data. Furthermore, the SEM-PLS approach has been widely adopted in technology acceptance research grounded in the UTAUT2 model [12].

3. RESULTS AND DISCUSSION

The results and discussion section of this study presents the outcomes of the data processing and analysis of Maxim application user reviews obtained from the Google Play Store. The discussion encompasses the sentiment analysis results, the outcomes of the UTAUT2 dimension labeling utilizing the *Zero-Shot Classification* approach, and the evaluation of the relationships between the UTAUT2 constructs using the SEM-PLS method. All analytical findings are subsequently discussed to explain user opinion tendencies and the critical factors that influence the acceptance and usage of the Maxim application

3.1 Distribution of Maxim User Sentiment Analysis Results

The distribution of sentiment analysis results was conducted to determine the emotional tendencies contained within the user reviews of the Maxim application. This analysis categorized the reviews into three primary groups: positive, negative, and neutral sentiments. Based on the data processing of the 2.000 review entries, it was revealed that negative sentiment was the most prominent with 961 reviews (48.05%), followed closely by positive sentiment with 887 reviews (44.35%), and neutral sentiment with 152 reviews (7.60%).

Table 4. Distribution of Sentiment Analysis Results

Sentimen	Jumlah	Persentase
Negatif	961	48.05%
Positif	887	44.35%
Netral	152	7.60%
Total	2.000	100%

These findings indicate that negative sentiment is slightly more dominant than positive sentiment. This dominance implies that user complaints remain the primary topic within Maxim application reviews. Several frequently recurring issues encompass sudden fare alterations, *login* or payment system constraints, as well as difficulties during the order cancellation process and other technical disruptions. Nonetheless, the considerably high percentage of positive sentiment demonstrates that a substantial number of users still perceive the benefits of the application, particularly in terms of affordable pricing and ease of use.

3.2 Distribution of UTAUT2 Construct Labeling Results

The distribution of the UTAUT2 construct labeling results aimed to determine how user reviews represent the various dimensions within the UTAUT2 framework. Based on the classification outcomes utilizing the *zero-shot classification* method on 2.000 reviews, all data entries were successfully mapped into one or more dimensions under a *multi-label* mechanism. The frequency of dimension occurrences revealed that *behavioral intention* (1.301) and *use behavior* (1.269) were the most dominant constructs, followed by *facilitating conditions* (1.026) and *effort expectancy* (1.014).

Table 5. Distribution of UTAUT2 Construct Labeling Results

Konstruk UTAUT2	Frekuensi
Behavioral Intention	1301
Use Behavior	1269
Facilitating Conditions	1026
Effort Expectancy	1014
Price Value	560
Performance Expectancy	542
Social Influence	482
Hedonic Motivation	346
Habit	321

The dominance of these constructs indicates that user reviews focus extensively on usage intentions and actual behavior when operating the application. Furthermore, the high frequencies observed in *facilitating conditions* and *effort expectancy* imply that factors such as ease of use, system stability, and technical support serve as the primary concerns for users. The *price value* (560) and *performance expectancy* (542) constructs were situated at a moderate level, demonstrating that users also take into consideration the aspects of pricing and the application's perceived usefulness. Meanwhile, the *social*

influence (482), *hedonic motivation* (346), and *habit* (321) constructs exhibited lower frequencies, signifying that user reviews tend to concentrate heavier on personal, functional experiences rather than social influences or hedonic enjoyment aspects.

3.3 SEM-PLS Analysis Results on the UTAUT2 Model

This study conducted model testing utilizing the *Structural Equation Modeling–Partial Least Square* (SEM-PLS) method with the assistance of SmartPLS 4 software. This evaluation was performed to determine the structural relationships among the constructs within the UTAUT2 model toward behavioral intention and use behavior on the Maxim application. The method employed to test the significance of the relationships between constructs was *bootstrapping* within the SmartPLS 4 software to obtain the *path coefficient*, *t-statistic*, and *p-value* metrics. A research hypothesis is declared accepted if the *t-statistic* value is > 1.96 and the *p-value* is < 0.05.

Table 6. Bootstrapping Results Using SmartPLS 4

Variabel	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T-statistics (|O/STDEV|)	P-values
BI -> UB	0.642	0.642	0.018	36.167	0.000
EE -> BI	0.238	0.238	0.022	10.878	0.000
FC -> BI	0.351	0.352	0.019	18.744	0.000
FC -> UB	0.201	0.201	0.016	12.600	0.000
HB -> BI	0.066	0.066	0.013	4.982	0.000
HB-> UB	0.082	0.082	0.011	7.773	0.000
HM -> BI	0.021	0.021	0.016	1.303	0.193
PE -> BI	0.051	0.051	0.019	2.723	0.006
PV -> BI	0.042	0.041	0.016	2.674	0.008
SI-> BI	0.220	0.221	0.015	14.383	0.000

Based on the *bootstrapping* test results presented above, it can be determined that the majority of the significance tests for the inter-construct relationships within the UTAUT2 model demonstrate a significant influence on *behavioral intention* and *use behavior*. The relationship from the *behavioral intention* variable to *use behavior* exhibits a *t-statistic* value of 36.167 and a *p-value* of 0.000. This indicates that *behavioral intention* has a positive and significant influence on *use behavior*. This finding implies that a higher behavioral intention to utilize the Maxim application corresponds to a higher actual usage behavior of the application.

The relationship between the *effort expectancy* variable and *behavioral intention* exhibits a *t-statistic* value of 10.878 and a *p-value* of 0.000. This result indicates that the ease of using the Maxim application serves as one of the critical factors influencing user intentions to continue utilizing the service. Users tend to possess a higher behavioral intention when the application is easily understood and operated.

The subsequent variable relationship demonstrates that *facilitating conditions* has a significant effect on *behavioral intention*, with a *t-statistic* value of 18.744 and a *p-value* of 0.000. Furthermore, the impact of *facilitating conditions* on *use behavior* yields a *t-statistic* value of 12.600 and a *p-value* of 0.000. Both outcomes indicate a positive and significant influence, implying that operational support—such as system

stability, device compatibility, and application accessibility—substantially affects both the user intentions and the actual usage behavior of the Maxim application.

The relationship between the *habit* variable and *behavioral intention* obtains a *t-statistic* value of 4.982 and a *p-value* of 0.000, while the relationship between *habit* and *use behavior* achieves a *t-statistic* value of 7.773 and a *p-value* of 0.000. These findings indicate that a user's established routine of continuously operating the Maxim application can enhance both their behavioral intention and their actual technology usage behavior.

In contrast to the previous findings, the relationship between *hedonic motivation* and *behavioral intention* secures a *t-statistic* value of 1.303 and a *p-value* of 0.193. This specific result does not satisfy the predetermined significance criteria; hence, the hypothesis is declared rejected. This finding reveals that enjoyment or entertainment factors do not serve as a primary catalyst influencing user intentions to utilize the application.

The relationship from the *performance expectancy* variable to *behavioral intention* generates a *t-statistic* value of 2.723 and a *p-value* of 0.006. This finding indicates that the functional effectiveness of the application in supporting user activities exerts a positive and significant influence on the behavioral intention to adopt the Maxim application.

Additionally, the relationship between *price value* and *behavioral intention* yields a *t-statistic* value of 2.674 and a *p-value* of 0.008. This finding demonstrates that users carefully evaluate the alignment between the monetary costs incurred and the perceived benefits obtained from utilizing the Maxim application.

Meanwhile, the relationship between *social influence* and *behavioral intention* produces a *t-statistic* value of 14.383 and a *p-value* of 0.000. This result provides empirical evidence that social pressures and recommendations also exert a positive and significant impact on the users' *behavioral intention*.

Overall, the structural model evaluation utilizing the SEM-PLS method indicates that the constructs of *behavioral intention*, *effort expectancy*, *facilitating conditions*, *habit*, *performance expectancy*, *price value*, and *social influence* are proven to have a positive and significant influence on the respective dependent variables. Conversely, the *hedonic motivation* construct does not demonstrate any significant impact on *behavioral intention* within the context of Maxim application utilization.

CONCLUSION

This study successfully integrated sentiment analysis and UTAUT2 construct classification on Maxim application user reviews sourced from the Google Play Store, employing IndoBERT for sentiment classification and Zero-Shot Classification for UTAUT2 dimension labeling, with structural relationships examined through the SEM-PLS method. The findings address the formulated research questions in three key dimensions.

First, with respect to sentiment distribution, negative sentiment was found to be the most prevalent category (48.05%), slightly exceeding positive sentiment (44.35%), with neutral sentiment accounting for the remaining 7.60% of the 2.000 reviews analyzed. This result indicates that, despite the widespread adoption of the Maxim application, user dissatisfaction — particularly related to fare inconsistencies, login and payment system

failures, and order cancellation difficulties — remains a dominant concern that warrants attention from application developers.

Second, regarding UTAUT2 construct distribution, the Zero-Shot Classification approach successfully mapped all 2.000 reviews into the corresponding UTAUT2 dimensions through a multi-label mechanism. The constructs of behavioral intention (1.301) and use behavior (1.269) emerged as the most frequently represented dimensions, followed by facilitating conditions (1.026) and effort expectancy (1.014). These findings suggest that user reviews predominantly reflect actual usage experiences and intentions, while hedonic motivation (346) and habit (321) were the least represented constructs, indicating that personal functional concerns outweigh social and hedonic factors in user discourse.

Third, with respect to the SEM-PLS structural model evaluation, the results demonstrate that six out of seven UTAUT2 constructs — namely *behavioral intention*, *effort expectancy*, *facilitating conditions*, *habit*, *performance expectancy*, *price value*, and *social influence* — exert a positive and statistically significant influence on their respective dependent variables. Notably, *behavioral intention* exhibited the strongest predictive power toward *use behavior* (t-statistic = 36.167, p-values = 0.000). In contrast, *hedonic motivation* failed to reach statistical significance in its relationship with *behavioral intention* (t-statistic = 1.303, p-values = 0.193), suggesting that enjoyment and entertainment-oriented factors do not constitute a primary driver of technology acceptance in the context of ride-hailing application usage.

From a theoretical standpoint, this study contributes to the existing literature by demonstrating the feasibility of combining NLP-based sentiment analysis with Zero-Shot Classification as an efficient and scalable alternative to questionnaire-based UTAUT2 studies, particularly for processing large-scale, real-world user-generated data in the Indonesian language context. The integration of IndoBERT, Zero-Shot Classification, and SEM-PLS provides a novel methodological framework applicable to future technology acceptance research.

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