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The Integration of Kansei Engineering and Kano Model on Natural Language Processing (NLP) to Support Development of Service Product in the Borobudur Temple Tourism

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***Abstract*— The Borobudur Temple Compounds is one of the spearheads of Indonesian tourism, anticipating introduction to the international community. Currently, the management of the compound is focused on maintaining the existing condition of tourism and increasing enthusiasm among visitors to experience the temple area. Amidst the challenges posed by the COVID-19 pandemic, the management has implemented stringent health procedures to ensure the safety and health of visitors. Therefore, this study aimed to investigate the service required to increase visitor enthusiasm and satisfaction in the Borobudur Temple Compounds using the Natural Language Processing (NLP) method to extract visitor sentiments as Kansei words from TripAdvisor. The results obtained were processed using Kansei Engineering type 1 to determine the most critical service quality category through Kano model. The integration of NLP, Kansei Engineering, and Kano model proved effective, showing attributes like popular Tripadvisor searches, such as exit, morning, temple, sunrise, and heat. Other attributes not listed but considered necessary based on Kansei Engineering and Kano model integration were identified, such as ticket prices, elephant enclosure management, and pamphlets. Based on the results, it was discovered that the management of Borobudur Temple Compounds needed to improve in two main aspects. These included the distance between each facility and the compound elephant cage, considered unenjoyable.**

***Keywords*— Natural Language Processing (NLP); Kansei engineering; Kano model; Borobudur temple.**

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I. INTRODUCTION

The tourism sector in Indonesia exhibits a consistent upward trajectory in terms of its revenue and gross domestic product (GDP) figures [1]. Nevertheless, according to the 2019 Travel and Tourism Competitiveness Index (TTCI) of The World Economic Forum (WEF), Indonesia lags behind Thailand, Malaysia, and Singapore among Southeast Asia countries in the tourism sector. Consequently, several strategies were devised 2017 to increase visitor numbers, leading to the initial development of ten priority travel destinations [2], [3]. These strategies were revised in 2019, focusing on five priority travel destinations [4], including Lake Toba (North Sumatra), Borobudur (Central Java), Mandalika Lombok (West Nusa Tenggara), Manado-Likupang-Bitung (Southeast Sulawesi), and Labuan Bajo (East Nusa Tenggara). The development of these five destinations is intended to boost the tourism sector, a significant industry that allows foreign exchange, creates employment, and increases local economic growth.

Among five priority travel destinations, the Borobudur Temple Compounds is one of the world's most enormous Buddhist structures located in the Kedu Valley, in the southern section of Central Java, Indonesia. Borobudur is known as the largest Buddhist temple ruin in the world [5]. Every year, Southeast Asian pilgrims visit this sacred site on a distant mountaintop [6]. Apart from Bali, the compound has been the central tourism destination in the country, particularly for domestic tourists. Data from the Central Bureau of Statistics shows that the number of visitors to the compound has increased by 2-5% consistently from 2015 to 2019, followed by a significant decrease in 2020 due to the COVID-19 pandemic [7]. Since the conclusion of 2021, the number of visitors has increased by 52% compared to the corresponding period in 2020 [8], showing a resurgence in the tourism industry. Currently, the management of the

compound is focused on maintaining the existing condition of tourism and increasing visitors' experience. The management has also implemented strict health procedures to ensure the safety and health of visitors during the COVID-19 pandemic.

Tourism, in specific, has seen significant transformations because of the emergence of social networks and the rapid advancement of new technology [9]. Previously, tourist preference analysis is conducted using survey which might lead to sampling bias [10]. Nowadays, several online platforms have provided spaces for people to express their travel experiences and opinions, which is known as knowledge sharing. The generated content from the online platforms provides important customers data that is available, spontaneous, insightful and low cost [11]. According to Zhao et al. [12], service industries should focus on textual reviews containing subjective words. Yousaf and Kim [13] stated that online reviews offer profound and real-time understanding, serving as a valuable tool for assessing the future development of the tourism management. Although the Borobudur Temple Compounds has good reviews, some negative feedback capable of reducing the enthusiasm of visitors can be an obstacle for management. For example, the compound is rated 4.7 stars (out of 5) from 85,395 reviews on Google, 8.8 (out of 10) from 1,844 reviews on Traveloka, and 4.5 stars (out of 5) from 7,552 reviews on TripAdvisor. In service industries related to tourism, online reviews, and ratings have high significance from the visitors' perspectives.

Several studies have been conducted using numerous methods, including naïve bayes, to understand people needs based on their social media activities, complaints, or reviews [14], [15], [16], [17], neural network [15], [18], Natural Language Processing (NLP) [19], [20], [21], [22], [23], [24], multimodal analysis [25], machine learning [26], [27] or combination of some methodologies [28]. The results showed that the availability of textual reviews was beneficial, providing better data acquisition, less time-consuming, and guaranteeing data authenticity [29]. Due to the high number of reviews, this study proposed text mining by integrating NLP as a tool to convert everyday language into a format understood by machines. Moreover, NLP is a branch of artificial intelligence that deals with the interaction between computers and humans using natural language [20]. Studies using the lexicon and NLP methods have been used to screen for symptoms of depression among Twitter users, yielding better accuracy compared to machine learning [30]. The term "lexicon" refers to a component of NLP system that holds semantic and grammatical information about individual words or strings [31].

Numerous studies have explored the integration of NLP, Kansei Engineering, and Kano model. Jiao and Qu [32] conducted a study that integrated NLP and Kansei Engineering, using deep semantics and syntactic structures to extract pure Kansei knowledge. The results in the form of frequency distributions and associations accelerate traditional product surveys and refine users' emotions. Furthermore, Hou et al [33] desegregated the ability of NLP by mining online reviews on particular product and using the ability of Kano model to classify preferences of product attributes and improvement. Although models showed the ability to improve product, there is a need to understand new visitors' voices to ensure the relevance of newly developed product. Kano model in product development could classify five costumer's needs and requirements, including must-be, one-dimensional, attractive, indifferent, and reverse [29]. According to Chen et al. [34], Kano model could help decision-makers understand the relationship between customer satisfaction with product attributes, as stated by Bi et al. [35], Gan et al. [36], Lai et al. [37], Liu et al. [38], Avikal et al. [39], and Asian et al. [40]. The integration of Latent Dirichlet allocation and Kano model has also been proposed by Bi et al. [35] to understand visitors satisfaction. The model proposed focused on understanding customer sentiment, extending further to improve product's attributes. Avikal et al. [39] also proposed Kano model to improve visitors' satisfaction by developing product with high aesthetic attributes, including SUV cars. Although only focusing on one attribute, the usage of the Kano model resulted in better visitors' satisfaction. This unique characteristic is attributed to the capacity to evaluate business partners, as proposed by Asian et al. [40], where third-party logistics was selected based on Kano model evaluation.

Kano model has also been used for extracting product attributes of customers' demands based on online reviews, proposed by Zhang et al. [41]. Study by Jin et al. [42], product development has promising results by integrating Kansei Engineering and Kano model. This integration enables the capturing of visitors' emotional demands and the generation of actionable insights for effective design.

The integration between Kansei Engineering and Kano model has been explored but the specific application in tourism sector is limited. Hartono [43] combined service quality tools with Kansei Engineering to identify the discrepancies between perceived and predicted service for Indonesian tourists. The result shows that the emotional aspect, such as happiness, peacefulness, or relaxedness is more important compared to the cognition aspect, including elegance or attractiveness. Hsiao et al. [44] also proposed Kansei Engineering to evaluate hotel service in Taipei based on online reviews, specifically the improvement of facilities to accommodate the demand of international tourists. Furthermore, Sugiyama et al. [45] used the morphological analysis tool NLPIR (Natural Language Processing and Information Retrieval) to identify international visitors' emotions regarding the trip to Japan.

Based on the background above, this study emphasizes NLP method as a basis for obtaining data extraction related to visitor satisfaction and priorities required to be improved according to the integration of Kansei Engineering and Kano model into the Borobudur Temple Compounds. As an ergonomic method for visitors-oriented product/service development, Kansei Engineering can translate subjective user perceptions into design specifications [46]. Consequently, this study proposes using Kansei Engineering to generate design recommendations based on the emotional states and needs of visitors. The use of Kansei Engineering method requires the integration with others from marketing, psychology, and statistics, applying multiple phases and various instruments. For the analysis, the Kano model was used to determine the importance of changes made, while Kansei word retrieved was applied to prioritize the amenities that the compound needed to create. The Kano model is a philosophy that focuses on the desires and requirements of people to build goods and services, while Kansei Engineering

is a system converting impressions into product characteristics. The integration of NLP with Kansei Engineering and Kano model is expected to facilitate the understanding of customer requests and expectations, thereby enhancing the quality of service at the Borobudur Temple Compounds.

II. Material and Method

This study proposed a framework to develop and improve service products in the Borobudur Temple Compounds using the integration of NLP, Kansei Engineering, and Kano model. Firstly, reviews were obtained from TripAdvisor, which served as a travel study platform collecting and organizing user ratings and reviews on tourism as well as hospitality service worldwide. All the reviews obtained were from 1 January 2019 – 1 September 2021 and classified using NLP Secondly, after classification, several Kansei words were selected according to the classification and association results conducted with NLP. Thirdly, service attributes are developed based on Kansei words and a survey was performed. The results were used to categorize service attributes into [a] must be improved by the management, [b] one dimensional, and [c] indifferent. Moreover, the study framework is shown in Figure 1.

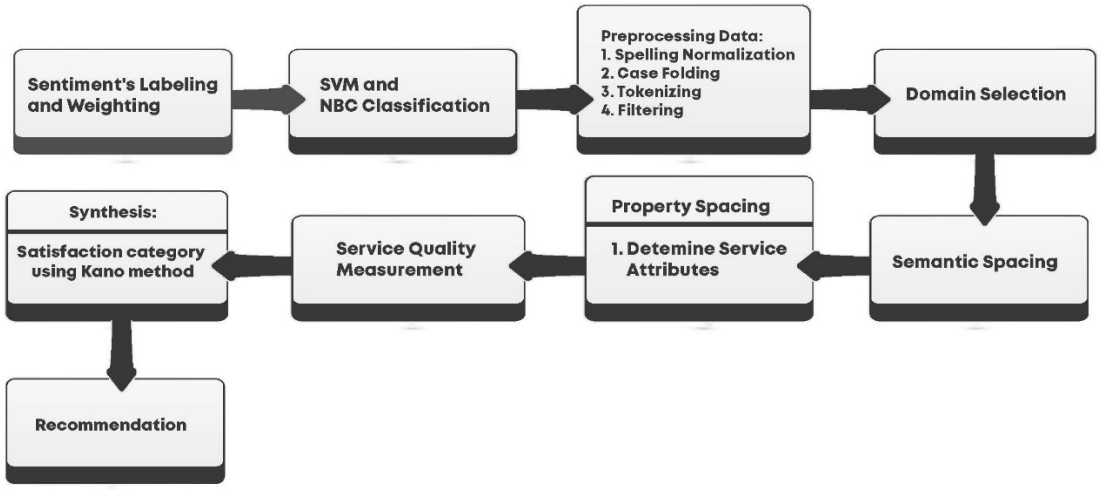
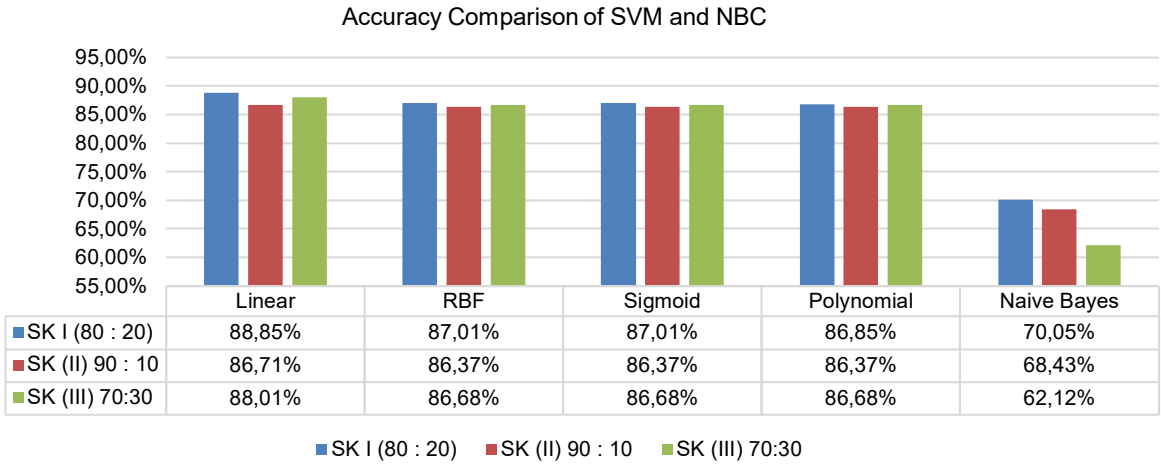


Fig. 1 Framework integration NLP, Kansei Engineering, and Kano Model

A. NLP

All reviews collected were pre-processed before classification to ensure that only the keywords were captured for the next procedure. The pre-processing steps carried out included normalization, case folding, tokenizing, and filtering. This was followed by the integration of the lexicon-based method, a dictionary of opinion words was made to identify positive and negative words in a sentence. Lexicon-based sentiment analysis is a method of using a dictionary that integrates the polarity of words to determine sentiment [47]. Furthermore, lexicon-based is capable of extracting opinion sentences with very high precision, conveying the language's permanent semantic features as well as the collocational properties of certain text [31].

The classification was carried out to separate negative and positive sentiments from the reviews. In this process, two methods, Support Vector Machines (SVM) and Naïve Bayes Classifier (NBC), were used, yielding the best results with minimum error selected. Subsequently, three data testing configurations were used to ensure optimal accuracy, with data training and testing of 70:30, 80:20, and 90:10. Based on two methods performed, the results showed that SVM with kernel linear and ratio data of 80:20 had the highest accuracy, as presented in Figure 2.



	Linear	RBF	Sigmoid	Polynomial	Naive Bayes
SK I (80 : 20)	88,85%	87,01%	87,01%	86,85%	70,05%
SK (II) 90 : 10	86,71%	86,37%	86,37%	86,37%	68,43%
SK (III) 70:30	88,01%	86,68%	86,68%	86,68%	62,12%

Fig. 2 Comparison of Classification Performance of SVM and NBC

The average total accuracy of the SVM method showed an error of more than 12%, indicating the need for minimization. This discrepancy could be attributed to the type of sentiment class labeling used. In this study, the sentiment detection between words used a lexicon dictionary, where analysis was carried out without any categorization based on sentence structure, such as nouns, verbs, and adjectives. For example, the word "dislike" in this sentence structure has the word "no," with a negative sentiment, while "likes" shows a positive sentiment. All the positive and negative sentiments were sorted accordingly, and an association rule was performed to capture the specific words following the selected sentiment. Subsequently, negative sentiment was used as a guide for the next data extraction because positive sentiment was considered a sign that visitors were satisfied with service. In total, there were nine words association that had the highest lift ratio (>1).

B. Kansei Engineering

The accurate expression of visitors' emotional needs for product is implicit, imprecise, and ambiguous, posing a challenge for academic study and product development. Therefore, integrating users' emotional needs into product design has become a focus. This stage is carried out through three main steps, namely, i) collecting Kansei words, ii) selection, and iii) data collection. Kansei words could be found by developing a series of measurement methods based on the interpretations made when NLP was used to process data. The essence of determining service attributes originated from Kansei words obtained from the previous semantic space stretch and the accompanying words. For example, the first Kansei words were "expensive", with cost and tourist, followed by two service attribute sentences containing "cost" and "tourist" with the adjective "expensive" being formulated. However, some adjustments were made since service attributes needed to be in positive words. This study used Kansei Engineering Type I to break down the concept of the targeted product/service into more detailed concepts and developed into several levels, interpreted in terms of the physical characteristics of product design. Moreover, there is a need to identify all product or service attributes and select those with the greatest potential impact on the development of the Borobudur Temple Compounds. In this stage, 11 attributes were created according to Kansei words.

C. Kano Model

After selecting service attributes, two questionnaires were developed to assess the perceived importance by users and the satisfaction level of visitors to the Borobudur Temple Compounds. The questionnaire used the Semantic Differential Scale with a 5 rating. Subsequently, Kano data was obtained from a service importance questionnaire, which included two kinds of questions, namely Functional and DysFunctional. Validity and reliability tests were performed to ensure questions asked were valid and reliable. The results of the validity test showed that the Corrected Item-Total (r) for both questionnaires exceeded 0.278. Based on the reliability test, Cronbach's Alpha value of the degree of importance and satisfaction was 0.772, while the Functional and Dysfunctional Kano questionnaires were 0.732 and 0.705, respectively.

D. Integration of Kansei Engineering with Kano Model

The synthesis stage was carried out to categorize Kansei words according to service attributes with determined weight. With Kano model, the categorization was based on the ability of product/service to satisfy visitors needs by matching Functional and Dysfunctional answers. According to Kano et al. [48], there are 3 types of service attribute levels that affect visitors' satisfaction, namely attractive, one-dimensional, and must-be. Specifically, attractive attributes are unexpected service that led to high satisfaction when provided. One-dimensional is a category of services, required to be fulfilled by consumers, with a level of satisfaction proportional to the performance of service. This shows that better service performance will result in a higher level of visitors' satisfaction, and vice versa. Must-Be (Must Exist) is a service category which when not fulfilled, visitors will be very disappointed and potential loss of repeat business.

Existing weighting was carried out to determine the weight of service attributes formed using service quality (SERVQUAL) method developed by Parasuraman et al. [49]. This method assesses the quality (Q) that has been given by the compound to visitors, across various domains including online platforms [50], banking [51], and hospitality [52], [53]. The value of Q can be obtained from the quotient between the weight of reality (P) and expectation (H) obtained from the previous questionnaire. The actual weight (P) is the actual condition felt by visitors, while the expectation (H) is the initial perception before visiting. Moreover, a smaller gap (G) between reality and expectations shows better orientation within imagined and expected experiences at the compound. Regarding the quality value (Q), when the value obtained is equal to one, service quality is categorized as good. The final stage of data processing was carried out by determining the categorization of service attributes for developing service offered by the compound based on the results of Kansei and Kano integration. After determining visitors' needs according to Kano method, classification for each service attribute is determined using Blauth's Formula.

III. Results and Discussion

A. NLP, Kansei words, and Kansei Attributes

After conducting the classification and association, Kansei words were extracted from the association results, with the qualification value of lift > 1 and the conviction value set to inf (infinite). From the negative sentiment, a total of 560 associations were identified, resulting in 9 Kansei words. This occurred because many associations were deemed inappropriate when used as Kansei words such as "java", "miracle", "site", "climb engraving", etc. The confusion of the association was attributed to the omission of several conjunctions during the "filtering" process in the pre-processing stage, along with results failing to meet the criteria such as lift values <1. Kansei words selected are shown in Table 1.

The property space was stretched in the form of service attributes derived from Kansei words pair in the previous association. From these pairs, a sentence representing Kansei words was developed to obtain 11 service attributes as listed in Table 2. In service attributes, Kansei words were divided into two, namely "cheap", and "enjoy". For "cheap" two

attributes were created due to different entrance prices for local and foreign visitors at the Borobudur Temple Compounds. Regarding "enjoy", two attributes "elephant" and "rising" were identified to capture visitors enjoyment of sunrise and the experience at the "elephant cage" facilities at the compound. The list is ordered according to the higher gap value calculated using the SERVQUAL method.

TABLE I
KANSEI WORDS LIST

Kansei Word
expensive >< cheap
enjoyable >< bored
beautiful >< ugly
tired >< relaxing
far >< near
crowded >< quiet
good >< bad
available >< unavailable
hot >< cold

TABLE II
KANSEI WORD LIST

Number	***Kansei* Attribute**
X2	Cheap Borobudur fees for foreign tourists
X11	There is a visitor guide (user guide/pamphlet)
X6	Visitors do not have to go through the shopping area near the parking lot
X7	Walking in the Borobudur Temple Is Not Tired and Hot
X4	The Elephant Cage is well cared for, so it can be enjoyed
X1	Cheap Borobudur fee for local tourists
X3	Visitors can enjoy the Rising View
X10	Availability of transportation between the Borobudur temple facilities
X5	Beautiful Borobudur Temple Sunrise View
X8	Good road condition
X9	The way out of temple is full of sellers

B. Result on Kansei Engineering and Kano Model Integration

The Kano model serves as a sophisticated framework in understanding how different service attributes influence visitor satisfaction levels within the context of tourism, specifically in the management of the Borobudur Temple Compounds. By assessing the relationship between the level of fulfillment of each service attribute and the corresponding level of visitor satisfaction, the model provides a nuanced insight into which aspects of service and facility management are crucial for enhancing the visitor experience. It helps in pinpointing the critical areas that require immediate attention and improvement, thereby enabling the compound management to prioritize resources effectively. The model categorizes service attributes into three distinct categories: Must-Be (M), One-Dimensional (O), and Indifferent (I), each signifying a different impact on visitor satisfaction and highlighting the varied nature of visitor expectations.

Must-Be (M) attributes are considered fundamental requirements that, if unmet, lead to significant dissatisfaction among visitors. These are the essential services or features that visitors expect as a given when they visit the Borobudur Temple Compounds. On the other hand, One-Dimensional (O) attributes exhibit a direct correlation between their level of performance and visitor satisfaction; improvements in these areas are likely to enhance visitor satisfaction linearly. Lastly, Indifferent (I) attributes are those that do not significantly affect visitor satisfaction, whether present or absent. These classifications allow the management to strategically focus their efforts on attributes that will have the most substantial impact on improving the overall visitor experience, ensuring that resources are allocated to areas that will enhance satisfaction most effectively.

As shown in Table 3, the Must-Be category represents an essential requirement for visitors. Service attributes in this category were considered essential for visitors and required prioritization by the Borobudur Temple Compounds. For example, the X6 attribute has a quality value of 0.566, showing that the considerable distance between the places/facilities in the compound could result in visitors fatigue when ignored. The X4 attribute has a quality value of 0.706, showing that visitors are unable to enjoy the "elephant cage". Regarding X5 and X9, quality value 1 showed that visitors were satisfied with the view of the compound and the exit was empty of sellers. Additionally, the results obtained from X9 showed the current condition, where the road was no longer crowded with sellers.

TABLE III
KANSEI AND KANO INTEGRATION RESULT

No	Gap P-H	Quality (Q) =P/E	*Kano*	*Kansei Word*s
X6	-1.76	0.566	M	near/close
X4	-0.98	0.706	M	enjoy
X5	0.18	1.041	M	beautiful
X9	1.88	1.681	M	crowded
X2	-2.48	0.376	O	cheap
X11	-1.82	0.547	O	available
X7	-1.46	0.669	I	tired, hot
X1	-0.46	0.841	I	cheap
X3	-0.5	0.873	I	enjoy
X10	-0.48	0.877	I	near
X8	0.2	1.045	I	good

The one-dimensional attribute is considered important due to its direct impact on visitors' satisfaction. Therefore, service providers are required to consider these attributes to avoid visitors being disappointed. The X2 attribute has a quality value (Q) of 0.547, showing the perception of visitors regarding the high price set by the Borobudur Temple Compounds management. Specifically, the Entrance Ticket Price (HTM) set for foreign visitors is $25 or 350 thousand, which is seven times higher compared to local visitors. Attribute X11, with a quality value of 0.54, shows the absence of visitors guide commonly used when enjoying the compound. The contents of the guide can be in the form of a map, with an explanation of both the facilities and history of the compound. Moreover, this attribute is included in One-Dimensional category that must be fulfilled to enhance visitors' satisfaction.

Visitors' satisfaction is not influenced by the nature of the product whether is functional or non-functional. Moreover, good or bad service attributes categorized as indifferent have no significant visitor's satisfaction. In this study, there are 5 service attributes that fall into the Indifferent category. The innovative integration of NLP with Kansei Engineering and the Kano model has unveiled a nuanced understanding of

visitor experiences and expectations at the Borobudur Temple Compounds. This approach has successfully highlighted several service attributes, such as "exit," "morning," "temple," "sunrise," and "heat," aligning closely with popular search terms on TripAdvisor. This alignment not only validates the effectiveness and relevance of the integrated methodology in pinpointing key aspects of the visitor experience but also demonstrates how visitor feedback, captured through digital platforms, can mirror the actual preferences and pain points experienced on-site. Such insights are invaluable, as they provide a direct link between the sentiments expressed by visitors in their reviews and the service attributes that significantly impact their experience at the temple compounds.

However, it's essential to note that the focus on negative sentiments during the data extraction phase means that several potentially significant keywords may not have been highlighted in the study's results. These omitted words could represent aspects of the visitor experience that are either viewed positively or considered neutral, and thus, were not captured in the analysis focused on negative feedback. This exclusion underscores a critical limitation of the study's methodology, suggesting that a comprehensive analysis that includes positive and neutral sentiments could provide a more holistic view of visitor experiences. By omitting these sentiments in the pre-processing stage, there's a risk of overlooking important attributes that contribute to satisfaction and enjoyment, highlighting the need for a more inclusive approach to data analysis in future research efforts.

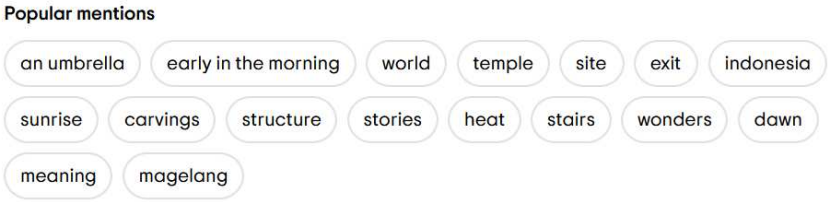


Fig. 3 Popular Mention

IV. Conclusion

The study embarked on an innovative journey to enhance the visitor experience at the Borobudur Temple Compounds by intertwining NLP with Kansei Engineering and the Kano model. This multifaceted approach began with the expansion of the semantic space to effectively process visitor sentiment data. The initial stages involved meticulous pre-processing of the data, followed by sentiment classification utilizing SVM and Naive Bayes techniques. These methods were instrumental in distilling the vast and varied sentiments of visitors into coherent, actionable insights, setting the stage for the subsequent integration with Kansei Engineering and the Kano model.

Upon completing the sentiment analysis, the study progressed to defining the attribute space by assessing service quality and integrating it with Kansei Engineering and the Kano model. This crucial phase aimed at identifying the attributes that significantly influence visitor satisfaction. Through the integration of these methodologies, the research pinpointed the priorities that yielded the highest levels of satisfaction according to the Kano model's classification. Remarkably, the extraction of data from the negative sentiment group through NLP classification revealed eight Kansei words - "cheap," "enjoyable," "beautiful," "relaxed," "close," "quiet," "good," and "available." These keywords encapsulate the essential elements desired by visitors, offering a clear direction for enhancing their experience at the Borobudur Temple Compounds.

The integration of NLP with Kansei Engineering and the Kano model in enhancing the visitor experience at Borobudur Temple Compounds has proven to be effective, as evidenced by the convergence of the identified service attributes with the popular search terms on TripAdvisor. Terms such as "exit," "morning," "temple," "sunrise," and "heat" were among the attributes that aligned with the visitors' sentiments and preferences. This alignment not only validates the effectiveness of the integrated approach in capturing the essential elements of the visitor experience but also underscores the importance of leveraging online platforms to gauge visitor interests and expectations. The matching attributes between the study's findings and the popular searches highlight the relevance of the integrated approach in identifying key factors that influence visitor satisfaction.

Furthermore, the study unearthed additional attributes not commonly mentioned in popular searches but deemed crucial for enhancing the visitor experience, such as ticket prices, elephant enclosure management, and the availability of pamphlets. These findings suggest that while some aspects of the visitor experience are well-recognized and frequently discussed, others may not be as visible but are equally important. The dissatisfaction expressed by some visitors regarding the walking distance between facilities within the compound and the management of the elephant enclosure points to areas requiring immediate attention. These insights, derived from the integration of NLP with Kansei Engineering and the Kano model, offer a comprehensive understanding of visitor sentiments, highlighting both strengths and areas for improvement in the overall management of the Borobudur Temple Compounds.

In response to the insights garnered from the integration of NLP Kansei Engineering, and the Kano model at the Borobudur Temple Compounds, targeted recommendations have been proposed to elevate the tourism services offered. One significant recommendation is the provision of pamphlets to visitors upon their arrival. These pamphlets would serve not only as guides to navigate the extensive temple compounds but also as educational tools, enriching the visitor experience with historical insights and detailed

descriptions of the site's architectural marvels and cultural significance. This initiative aims to enhance visitor engagement and satisfaction by making the exploration of the temple more informative and accessible. Additionally, the study underscored the importance of improving the welfare and management of elephants within the temple compounds. Recommended enhancements include increased attention to the elephants' diet, living conditions, and overall health. By ensuring that these majestic creatures are well-cared for, the temple can enhance its ethical stance and attract visitors who value animal welfare. Furthermore, revising the admission pricing strategy through the willingness to pay method has been suggested. This approach would involve assessing visitors' readiness to pay for their experience, ensuring that ticket prices reflect the value offered while remaining accessible. These recommendations, if implemented, could significantly contribute to the sustainable development of tourism at the Borobudur Temple Compounds, ensuring that it remains a cherished destination for future generations.

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