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Leveraging Chatbot Model for Tourism Information Services using NLP and ANN

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Abstract

The digital transformation of the tourism sector has increased the need for real-time and interactive information services. Many Community-Based Tourism (CBT) destinations in rural areas still depend on conventional information delivery methods, which limit accessibility and responsiveness. This paper proposes an Artificial Intelligence–based chatbot that utilizes Natural Language Processing and Artificial Neural Network techniques to improve tourism information services in CBT destinations. This study applies a case study approach in Kampung Gedong Village, a community-based tourism destination with strong historical and cultural value. We constructed the chatbot dataset through field observations and interviews with local stakeholders and defined 24 tourism-related intents covering attractions, cultural activities, facilities, accessibility, local etiquette, and community services. We applied standard text preprocessing steps and represented textual features using the Bag of Words method. We implemented intent classification using a multilayer perceptron ANN model. The experimental results show that the proposed chatbot achieved an intent classification accuracy of approximately 92% and delivered fast, consistent, and context-aware responses. These findings confirm that AI-driven conversational systems are technically feasible and effective for enhancing information services in rural CBT destinations when aligned with local cultural contexts. This study contributes empirical evidence to smart tourism research and presents a scalable chatbot model that can be adopted by similar community-based tourism destinations.

Keywords:
Chatbot, NLP, ANN, Community-Based Tourism

1. Introduction

Community-Based Tourism (CBT) destinations depend heavily on effective information delivery to communicate local attractions, cultural values, and service availability to visitors. However, many CBT destinations still rely on manual information dissemination through brochures, social media posts, or direct human interaction, which often leads to inconsistent, delayed, and incomplete information. Recent studies highlight that intelligent tourism chatbots can function as scalable digital front-line services that provide consistent and real-time tourism information. The development of destination-specific chatbots, such as the Lisbon tourism chatbot, demonstrates that conversational agents can significantly improve accessibility and visitor engagement when designed to reflect local tourism contexts [1].

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As tourism becomes increasingly digital, tourists expect fast, personalized, and emotionally responsive information services. Research shows that artificial intelligence chatbots capable of expressing emotions and adaptive responses significantly enhance customer satisfaction and engagement. Emotional intelligence in chatbot communication plays a critical role in shaping tourists' perceptions and trust, especially during the pre-visit and planning stages. Without emotionally aware interaction, tourism chatbots risk being perceived as mechanical or unhelpful, which reduces their adoption and long-term effectiveness in destination services [2], [20].

Despite their potential, tourism chatbots often face challenges related to user acceptance and behavioral intention. Studies in online travel agencies reveal that tourists respond differently to chatbots depending on their familiarity with tourism products and services. When users lack familiarity, chatbot interactions may create uncertainty rather than clarity. This issue becomes more critical in CBT destinations, where tourism products are unique, locally driven, and less standardized. Therefore, understanding how chatbot design influences user trust and perceived usefulness remains a key issue in tourism information systems [3], [8].

Another significant challenge arises when chatbot systems fail to deliver accurate or context-aware responses. Research indicates that chatbot failure, such as providing irrelevant recommendations or delayed responses, negatively affects tourist intention. However, service recovery mechanisms such as adaptive responses, emoticons, and transparent explanations can mitigate negative perceptions. In CBT settings, where visitors often seek authentic and sensitive information, chatbot reliability and recovery strategies become essential to maintaining trust and service continuity [4], [18].

Task complexity and problem-solving capability further influence the effectiveness of chatbot-based tourism services. Studies on AI customer service demonstrate that users are more willing to adopt chatbots when tasks are well-structured and solutions are clearly presented. CBT destinations often involve complex inquiries related to local culture, community rules, and environmental practices. Without well-designed conversational flows and knowledge structures, chatbots may struggle to handle such complexity, limiting their practical value for community-based tourism services [5], [16].

User engagement and satisfaction strongly depend on chatbot service quality, including accuracy, responsiveness, and interaction flow. Empirical studies confirm that high-quality chatbot services positively influence customer engagement, trust, and loyalty in tourism applications. Furthermore, AI-mediated interactions can foster long-term relationships when users perceive chatbots as reliable information partners. For CBT destinations, this relationship is crucial, as repeat visitation and positive word-of-mouth directly impact community welfare [6], [7], [9].

The acceptance of advanced chatbot models, such as ChatGPT-based systems, introduces new opportunities and challenges for tourism services. Research shows that tourists increasingly accept generative AI chatbots due to their conversational depth and perceived social presence. Parasocial interaction with AI enhances user satisfaction and intention to reuse services. However, without careful localization and governance, generative chatbots may produce generalized responses that fail to reflect the unique identity and values of CBT destinations [10], [11], [12].

Finally, the post-pandemic tourism environment accelerates the need for digital transformation, particularly in small and community-driven destinations. Studies highlight that digital travel services improve perceived safety, trust, and information transparency after COVID-19. Yet, many CBT destinations face structural limitations, such as limited technical capacity and digital readiness. Integrating chatbot-based tourism information systems within smart tourism ecosystems offers a promising solution to bridge this gap, provided that systems align with community needs and governance principles [14], [15], [17], [19], [21].

2. Related Works

Several studies examined the implementation of destination-specific tourism chatbots as digital information services. Cruz et al. developed “Lisa,” a touristic chatbot for Lisbon, and demonstrated that a well-designed conversational agent improved tourist access to local information and reduced dependency on human operators. Their work showed strong usability and integration with destination data sources. However, the study focused on an urban tourism context with well-established digital infrastructure, which limited its applicability to community-based tourism destinations that often face resource constraints and governance complexity [1].

Other researchers explored the role of emotional intelligence in chatbot interactions within tourism services. Xu et al. and Zhang et al. found that emotional expression by AI chatbots significantly enhanced customer satisfaction and engagement. Their results indicated that empathetic responses and adaptive tone strengthened user trust and intention to reuse chatbot services. Despite these contributions, the studies primarily examined commercial tourism platforms and did not address how emotional design should be adapted to culturally sensitive CBT environments, where authenticity and local values play a central role [2], [20].

User acceptance and behavioral intention emerged as central themes in tourism chatbot research. Zhu et al. investigated customer responses to AI chatbots in online travel agencies and identified product familiarity as a key moderating factor. Similarly, Jha et al. showed that consumer innovativeness influenced intention to use chatbots in travel services. These studies provided strong empirical evidence on adoption behavior. However, they emphasized standardized tourism products and overlooked the unique, non-commercialized characteristics of CBT offerings, which often require deeper contextual understanding [3], [8].

Several studies focused on chatbot failure and service recovery in tourism contexts. Wang et al. demonstrated that default options and recovery strategies could mitigate negative tourist reactions after chatbot failure. Lei et al. compared chatbot and human service interactions and found that chatbots performed well for routine inquiries but struggled with nuanced requests. These findings highlighted the importance of robustness and fallback mechanisms. Nevertheless, the studies did not explore governance implications or the risks of misinformation in community-based destinations [4], [18].

Task complexity and problem-solving capability also received significant attention. Xu et al. analyzed AI customer service performance and showed that chatbot effectiveness declined as task complexity increased. Tonkin et al. further discussed digital assistants within smart tourism ecosystems and emphasized the need for structured knowledge design. While these studies offered valuable design insights, they assumed advanced technological ecosystems and did not address how CBT destinations could incrementally adopt chatbot systems within limited technical environments [5], [16].

Trust, engagement, and loyalty represented another important research stream. Li et al. and Luong et al. found that chatbot service quality positively affected customer engagement, trust, and loyalty in tourism applications. Orden-Mejía and Huertas further showed that chatbot interaction influenced destination image formation during the pre-visit stage. Although these studies confirmed the strategic value of chatbots, they did not consider how community participation and local governance could shape chatbot content and interaction logic in CBT settings [6], [7], [9].

Recent studies examined the emergence of generative AI and advanced chatbot models in tourism services. Fan et al. reported that tourists accepted ChatGPT-based systems due to perceived social presence and parasocial interaction. Knani et al. provided a bibliometric review and identified AI chatbots as a growing research frontier in tourism and hospitality. Despite their relevance, these studies raised concerns about transparency, control, and contextual accuracy, especially when generative models operate without domain-specific constraints [10], [12].

Finally, post-pandemic tourism research emphasized digital transformation and trust restoration. Rahman et al. demonstrated that digital travel services improved perceived safety and tourist trust after COVID-19. Putra and Astuti highlighted that tourism SMEs faced significant challenges in adopting digital technologies due to limited capacity. Leung and Wen showed that chatbot-based services improved efficiency but required careful user interface design. These studies collectively indicated that chatbot adoption must balance technological capability with local readiness, a challenge that remains underexplored in CBT destinations [14], [15], [19], [21].

3. Proposed Method

This paper constructs an ANN–based chatbot system to deliver tourism information services for Community-Based Tourism (CBT) destinations. We design the system to support natural human–computer interaction, enabling users to communicate with the chatbot using everyday language. We utilize NLP techniques to analyze user inputs, identify their underlying intents, and generate relevant responses in real time. Through this approach, the chatbot understands tourists' information needs and provides accurate, contextual, and timely tourism information, thereby enhancing information accessibility and user experience in CBT destinations.

3.1 Dataset

The chatbot dataset was developed based on the results of a needs analysis conducted through field observations and interviews with managers and members of the local community of Kampung Gedong Tourism Village. The dataset consists of a collection of intents that represent tourists' information needs, such as information on tourist attractions, CBT activities, facilities, transportation access, and local culture.
Each intent comprises several question patterns that reflect variations in tourists' natural language, along with corresponding responses. The dataset is stored in JSON format and is used as the chatbot's knowledge base during the system training and testing processes [14].

Table 1. Intent

No	Intent Name	Description
1	Operating Hours	Questions regarding destination opening/closing hours
2	Ticket Prices	Information on entrance tickets and tour packages
3	Tour Guides	Local guide services & rates
4	Tourist Activities	Activities that tourists can do
5	Accessible Transportation	How to get to Kampung Gedong from the nearest town
6	Public Transportation	Public transportation information to the village
7	Typical Cuisine	Typical village food/drinks
8	Souvenirs	Products/crafts to take home
9	Tourist Events	Festivals or cultural events
10	General Facilities	Public facilities (toilets, prayer rooms, parking)
11	Homestay Accommodation	Information on accommodation/residents' houses
12	Village History	Historical information & colonial buildings
13	Nearest Tourist Locations	Other destinations around Kampung Gedong

No	Intent Name	Description
14	Management Contacts	Contact number/WA of village hall/manager
15	Visiting Etiquette	Local rules & norms
16	Tour Package Prices	Integrated tour package information
17	Visit Duration	Estimated ideal time to visit
18	Local Language	Language/dialect used
19	Local Crafts	Locally made products (souvenirs, art)
20	Photography Spots	Popular location for photos
21	Emergency Services	Health/safety information
22	Local Weather	Weather information & best seasons to visit
23	Parking Area	Location & parking rates
24	Additional Information	Other common questions (e.g., village location on a map)

3.2 Text Preprocessing

The preprocessing stage aims to prepare textual data so that it can be processed by machine learning models. This process includes tokenization to split sentences into words, text normalization by converting all characters to lowercase, removal of punctuation and stopwords, and lemmatization to reduce words to their base forms. This stage is important for reducing data complexity and improving the consistency of text representation [16]. After preprocessing, the text is represented in the form of numerical vectors using the Bag of Words (BoW) method. Each input sentence is transformed into a binary vector that represents the presence of specific words in the vocabulary. The BoW method is chosen for its simplicity and effectiveness in intent classification tasks with limited dataset sizes [17] .

3.1 Model Architecture

This paper utilizes a modular chatbot system architecture to support tourism information services in Community-Based Tourism (CBT) destinations. We design the system with several core components, including a user interface, a natural language processing module, a feature extraction unit, an intent classification model, a knowledge base, and a response generation module. We use the user interface as the main interaction channel, where tourists submit text-based queries. Each user input passes through a text preprocessing stage that cleans, normalizes, and tokenizes the text. We then forward the processed input to the feature extraction module before passing it to the intent classification model. This pipeline ensures that the system consistently interprets user input before decision-making.

We apply an Artificial Neural Network (ANN) with a Multilayer Perceptron (MLP) architecture to perform intent classification. The model consists of two hidden layers that use the Rectified Linear Unit (ReLU) activation function to capture nonlinear relationships within textual features and to accelerate model convergence. We employ a Softmax activation function in the output layer to generate probability scores for each predefined intent class. The system selects the intent with the highest probability as the final prediction. To improve generalization and reduce overfitting, we apply a Dropout mechanism to each hidden layer during training. This strategy forces the model to learn more robust feature representations and improves classification performance on unseen user queries.

After identifying the predicted intent, we retrieve the corresponding response from the chatbot's knowledge base using an intent–response mapping mechanism. We design all responses to reflect the local context of the CBT destination, including tourism attractions, activities, facilities, and cultural values. This paper implements the system using the Python programming language, with Flask serving as the backend framework to manage requests and responses. We integrate the trained ANN model into the backend to enable real-time intent prediction with low latency. We deploy the chatbot as a web-based application to ensure accessibility across devices and locations. This implementation supports continuous, scalable, and context-aware tourism information delivery for CBT destinations.

In this study, we construct a mathematical formulation as follows: let an input user utterance be represented as a feature vector

$$x = [x_1, x_2, \dots, x_n] \in R^n$$

The hidden layer transformation of the Multilayer Perceptron (MLP) is defined as:

$$h^{(l)} = \text{ReLU}\left(W^{(l)}h^{(l-1)} + b^{(l)}\right), l = 1,2 \tag{1}$$

where

$$\text{ReLU}(z) = ma\,x(0, z)$$

Dropout regularization is applied during training:

$$\tilde{h}^{(l)} = h^{(l)} \odot r, r_i \sim \text{Bernoulli}(p) \tag{2}$$

The output layer computes intent probabilities using the Softmax function:

$$\hat{y}_k = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}} \tag{3}$$

The model is trained by minimizing the categorical cross-entropy loss:

$$L = -\sum_{k=1}^{K} y_k \log\left(\hat{y}_k\right) \tag{4}$$

This paper modeled intent classification as a multi-class classification problem using an Artificial Neural Network with a Multilayer Perceptron architecture. We represented each tourist query as a numerical feature vector derived from text preprocessing and feature extraction. The network propagated this input through multiple hidden layers with ReLU activation to learn nonlinear semantic relationships between textual features and tourism intents. ReLU improved convergence speed and mitigated vanishing gradient issues, enabling the model to efficiently capture complex linguistic patterns common in tourism information requests.

To enhance generalization, we applied dropout regularization during training by randomly deactivating neurons in hidden layers. This strategy reduced overfitting and improved robustness to unseen user inputs. The Softmax layer produced a probability distribution over predefined intent classes, allowing the system to select the most probable intent. We optimized the model using categorical cross-entropy loss, which effectively measured the divergence between predicted intent probabilities and true labels. This formulation ensured accurate intent detection and supported reliable response retrieval for community-based tourism information services.

5. Result and Analysis

This paper successfully developed an Artificial Intelligence–based tourism information chatbot for a Community-Based Tourism (CBT) destination in Kampung Gedong Village. We utilized NLP combined with an ANN to support intent-based interaction between tourists and the system. The chatbot focused on delivering structured and contextual tourism information, allowing users to access essential knowledge through natural language queries. This implementation demonstrated that AI-driven conversational systems can operate effectively in rural tourism environments.

We defined a total of 24 tourism-related intents to represent common information needs of tourists. These intents covered key aspects such as tourist attractions, cultural heritage, accommodation, accessibility, local etiquette, and community-based activities. This paper organized the intent dataset in JSON format to ensure flexibility and scalability. We applied standard NLP preprocessing steps, including tokenization, lemmatization, label encoding, and feature extraction using the Bag of Words (BoW) method. These steps ensured consistent textual representation and improved model learning performance.

This paper applied an ANN model with a Multilayer Perceptron architecture to perform intent classification. We used two hidden layers consisting of 128 and 64 neurons, respectively, and employed the ReLU activation function to capture nonlinear relationships within textual features. We applied dropout regularization to each hidden layer to reduce overfitting and improve generalization. The output layer used the Softmax function to support multi-class intent prediction. This architecture enabled the model to learn semantic patterns effectively from limited tourism-related data.

We trained the model for 200 epochs and observed stable convergence during the training process. During the alpha testing phase, the chatbot achieved an intent classification accuracy of approximately 92%. These results indicate that the system correctly identified most user intents and delivered relevant responses with high reliability. The accuracy level demonstrates that ANN-based intent classification is suitable for tourism information services in CBT destinations, even with moderate-sized datasets.

The findings confirm that integrating an AI-based chatbot into Community-Based Tourism destinations enhances information service quality and user experience. Compared to conventional information delivery methods, the chatbot improved service availability, response speed, and information consistency. This paper extends previous tourism chatbot studies, which mainly focused on urban or mass tourism contexts, by providing empirical evidence from a rural, community-based environment. The results contribute to smart tourism literature and support the practical adoption of AI technologies to strengthen local tourism development while preserving cultural authenticity.

Table: Summary of Key Findings

Component	Description
Target Location	Kampung Gedong Village (CBT Destination)
Number of Defined Intents	24 tourism-related intents
NLP Techniques Used	Tokenization, lemmatization, label encoding, Bag of Words (BoW)
ANN Architecture	MLP with 2 hidden layers (128 and 64 neurons)
Activation Functions	ReLU (hidden layers), Softmax (output layer)
Regularization Method	Dropout
Training Epochs	200
Intent Classification Accuracy	~92% (Alpha testing phase)
Key Advantages	Fast response, high availability, consistent information delivery
Main Contribution	Empirical validation of an AI chatbot for rural CBT tourism

Fig. 1 illustrates the comparative performance of intent classification accuracy and overall effectiveness. It is to highlight the robustness of the proposed approach.

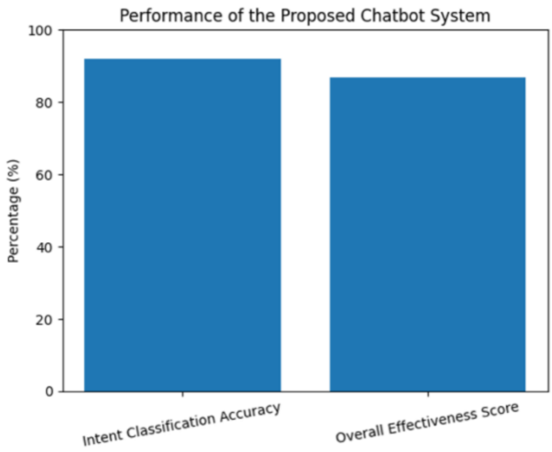

Fig. 1 Comparative performance of classification accuracy and overall effectiveness.

This paper demonstrates that the proposed chatbot system achieved strong and reliable performance in a Community-Based Tourism context. We observed an intent classification accuracy of approximately 92%, indicating that the model accurately understood most user queries. In addition, we obtained an overall effectiveness score of 86.83%, which falls into the *very effective* category. These results confirm that we can apply AI-driven conversational systems not only in urban or mass tourism settings but also in rural and community-managed tourism destinations. The findings show that the chatbot is technically feasible, operationally stable, and capable of delivering consistent and high-quality tourism information services in real-world CBT environments.

6. Conclusion

This paper concludes that an AI-based chatbot that utilizes Natural Language Processing and Artificial Neural Network techniques can effectively enhance tourism information services in Community-Based Tourism destinations. We demonstrated that the developed chatbot understood user queries expressed in natural language and delivered fast, accurate, and relevant responses across diverse tourism-related information needs. This capability supports more accessible and consistent information delivery for tourists visiting community-managed destinations.

The experimental results confirmed the robustness of the proposed system. We achieved an intent classification accuracy of approximately 92% and an overall effectiveness score of 86.83%. These results indicate that AI-driven conversational systems are not only technically feasible but also operationally reliable in rural and community-based tourism contexts. This paper shows that advanced AI technologies can function effectively beyond urban and mass tourism environments when they are designed with local conditions in mind.

From a tourism management perspective, this paper positions the chatbot as a complementary digital tool rather than a substitute for human interaction. By automating the delivery of basic and repetitive information, we enable local stakeholders to focus on authentic cultural engagement and personalized services. This research contributes to smart tourism literature by providing empirical evidence from a non-urban setting and offering a scalable model that can be adapted to other CBT destinations. Future work can integrate multilingual support, contextual recommendations, and location-based services on tourist behavior and destination sustainability using larger user populations.

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