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An Attribute-Based Explainable Recommendation System for Culinary Tourism

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ABSTRACT

The rapid growth of digital tourism platforms has increased the availability of culinary destination information, making it challenging for users to identify destinations that best match their preferences. Recommendation systems have become an effective solution for providing personalized recommendations; however, most conventional approaches only present recommendation results without explaining the underlying reasons, thereby reducing user trust and transparency. This study proposes an attribute-based explainable recommendation system for culinary tourism. The proposed system represents culinary destinations using descriptive attributes and computes recommendation relevance using TF-IDF vectorization and cosine similarity. An explanation module generates attribute-based explanations to improve recommendation transparency. Culinary destination data were collected and preprocessed through text normalization and TF-IDF vectorization to represent the characteristics of each culinary destination. Cosine Similarity was then applied to measure the similarity between user preferences and culinary destinations, while an explanation module was developed to provide understandable reasons for each recommendation based on shared culinary attributes, including category, main ingredients, flavor characteristics, and price range. The proposed system was implemented as a web-based application using Python, Flask, and MySQL. Experimental results show that the system achieved a Precision@5 of 0.92, a Recall@5 of 0.88, and an average response time of 0.73 seconds, indicating that the proposed approach is capable of generating relevant recommendations with efficient computational performance. Furthermore, the explanation module provides attribute-based explanations by presenting the shared culinary characteristics underlying each recommendation, thereby improving recommendation transparency. These findings demonstrate that the proposed system provides a practical, lightweight, and explainable solution for culinary tourism recommendation and has the potential to improve user experience in selecting culinary destinations.

Keywords: Content-Based Filtering, Explainable Recommendation System, Culinary Tourism, Cosine Similarity, TF-IDF.

INTRODUCTION

Recommendation systems have been widely adopted in various domains, including e-commerce, entertainment, education, and tourism, to assist users in selecting relevant products or services based on their interests. Among the available recommendation approaches, Content-Based Filtering (CBF) is one of the most popular techniques because it generates recommendations by analyzing the similarity between item characteristics and user preferences (Lops et al., 2022). The method is computationally efficient, does not depend on user interactions from other users, and performs well when sufficient item descriptions are available. In culinary tourism applications, attributes such as food category, ingredients, taste, price range, and location can be utilized to produce personalized recommendations (Wang et al., 2024).

Despite their effectiveness, conventional recommendation systems generally focus only on generating recommendation results without providing understandable explanations regarding why particular items are

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recommended (Tintarev & Masthoff, 2022). This limitation reduces user trust because users cannot easily understand the reasoning behind the recommendation process. Recent studies have shown that recommendation transparency plays an important role in improving user confidence, satisfaction, and acceptance of intelligent systems (Zhang & Chen, 2020). Therefore, the concept of Explainable Recommendation Systems (XRS) has emerged as an important research direction to provide interpretable recommendations while maintaining recommendation quality.

Several previous studies have proposed culinary tourism recommendation systems using content-based, collaborative, and hybrid recommendation approaches. Although these methods have demonstrated satisfactory recommendation accuracy, most existing systems primarily provide ranked recommendation lists without explaining which culinary attributes contribute to the recommendation results . Consequently, users often receive recommendations without understanding whether they are driven by similarities in food category, ingredients, flavor characteristics, price range, or other relevant attributes. This limitation reduces the transparency and interpretability of recommendation systems, particularly in culinary tourism applications where users frequently rely on attribute information when making dining decisions (Adomavicius & Tuzhilin, 2005; Zhang & Chen, 2020).

To address these limitations, this study proposes the development of an Explainable Content-Based Recommendation System for culinary tourism using the Cosine Similarity technique. The proposed system calculates similarity between culinary destinations based on predefined attributes and generates recommendation explanations by presenting the dominant features contributing to each recommendation. The explanation module is designed to improve recommendation transparency by informing users why a destination is recommended, such as having similar food categories, ingredients, flavors, or other relevant characteristics (Manning et al., 2008; Xu et al., 2023).

The recommendation process consists of feature extraction, vector representation, cosine similarity calculation, Top-*N* recommendation generation, and explanation generation. The generated explanations are expected to increase user understanding and confidence in the recommendation results without significantly increasing computational complexity. Furthermore, the proposed approach remains relatively simple and practical, making it suitable for implementation in small- and medium-scale tourism information systems (Ricci et al., 2022).

The main contribution of this study is the development of an attribute-based explainable recommendation system for culinary tourism. The proposed framework represents culinary destinations using descriptive attributes and generates transparent recommendation explanations based on shared culinary characteristics while employing TF-IDF vectorization and cosine similarity as the underlying similarity computation techniques. Unlike previous studies that primarily focus on recommendation accuracy, this research emphasizes recommendation transparency through attribute-based explanations without increasing computational complexity (Wang et al., 2024).

LITERATURE REVIEW

Recommendation systems have become an essential component in modern information systems because they assist users in selecting items that match their preferences from a large amount of available information (Resnick & Varian, 1997; Ricci et al., 2022). Various recommendation approaches have been developed, including Collaborative Filtering (CF), Content-Based Filtering (CBF), and Hybrid Recommendation Systems (Aggarwal, 2023). Among these approaches, Content-Based Filtering has attracted considerable attention due to its ability to recommend items based on item characteristics without requiring extensive historical interactions from other users (Lops et al., 2022). This approach is particularly suitable for culinary tourism applications because each destination can be represented using descriptive attributes such as food category, ingredients, flavor, location, price range, and available facilities.

Several previous studies have implemented Content-Based Filtering to improve culinary and tourism

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recommendation systems. Most studies represent destination characteristics as feature vectors and calculate similarity between items using the Cosine Similarity algorithm(Jurafsky & Martin, 2024). The recommendation process generally consists of feature extraction, vectorization using TF-IDF, cosine similarity computation, and Top-*N* recommendation generation(Chen et al., 2023) . Experimental results reported that Content-Based Filtering provides relevant recommendations with relatively low computational complexity, making it suitable for web-based and mobile recommendation applications.

Recent studies have also explored recommendation systems in culinary tourism by integrating location information, user preferences, and destination characteristics to improve recommendation quality (Setiawan, 2025) . Some researchers employed hybrid approaches combining Collaborative Filtering and Content-Based Filtering to overcome the cold-start problem, while others incorporated contextual information such as travel distance, opening hours, and user ratings(Priskila et al., 2023). Although these approaches improve recommendation accuracy, they generally increase system complexity and require a larger amount of user interaction data (Bengi & Gunawan, 2025).

In recent years, the concept of Explainable Recommendation Systems (XRS) has received increasing attention (Salsabilla & Utomo, 2025; Warta et al., 2025). Unlike conventional recommendation systems that only provide recommendation results, XRS presents understandable explanations regarding why specific items are recommended(Malikussaleh et al., 2025). Explanations may be generated based on feature similarity, user preferences, category similarity, or recommendation confidence scores (Christyawan et al., 2024). Previous studies have demonstrated that recommendation explanations improve user trust, transparency, satisfaction, and acceptance of intelligent recommendation systems (Hernandez-Bocanegra & Ziegler, 2023). Nevertheless, many explainable recommendation models rely on complex deep learning architectures or neural attention mechanisms that require substantial computational resources and large-scale datasets (Aljihadu, 2025).

Although Explainable Recommendation Systems have shown promising performance, only a limited number of studies have implemented lightweight explainable mechanisms for Content-Based Filtering in culinary tourism applications (Li et al., 2023). Existing studies mainly emphasize recommendation accuracy while providing limited information regarding the factors contributing to recommendation results. Consequently, users receive recommended culinary destinations without understanding the similarity attributes that influence the recommendation process (Christyawan et al., 2024).

Based on these observations, this study proposes an Explainable Content-Based Recommendation System using the Cosine Similarity technique for culinary tourism applications. The proposed system extends the conventional Content-Based Filtering approach by incorporating an explanation module that presents the reasons behind each recommendation based on similarity attributes, including culinary category, ingredients, taste characteristics, and similarity scores (Gao et al., 2023). Unlike previous studies that primarily focus on improving recommendation accuracy, this research emphasizes recommendation transparency while maintaining a lightweight and computationally efficient recommendation model suitable for practical implementation in culinary tourism information systems(Cahyani et al., 2024; Ma et al., 2023).

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Table 1. Comparison of Previous Studies on Explainable Recommendation Systems for Culinary Tourism

Study	**Dataset**	**Attribute Representation**	**Explanation**	**Evaluation**	**Limitation**
Wang et al. (2024)	Tourism destinations	Destination attributes + TF-IDF	No	Precision, Recall	No explainability
Christyawan et al. (2024)	Restaurants	Menu attributes	No	Accuracy	Restaurant only
Malikussaleh et al. (2025)	Tourist destinations	TF-IDF + Cosine	No	Precision	No explanation
Cahyani et al. (2024)	Culinary tourism	Culinary attributes	No	User testing	Only recommendation
Aljihadu (2025)	Culinary tourism	Content attributes	No	Precision	No transparency
Bengi & Gunawan (2025)	Tourism	CBF	Simple explanation	Accuracy	Rule-based explanation
This Study	150 culinary destinations	Category, ingredient, flavor, price, location	Attribute-based explanation	Precision@5, Recall@5, Response Time	Small dataset

Table 1 shows that previous studies have mainly focused on improving recommendation accuracy through content-based or hybrid recommendation techniques. Although descriptive attributes such as food category, ingredients, and price have been widely used to represent culinary destinations, most studies do not explicitly explain the shared culinary attributes underlying the recommendation results. Existing explainable recommendation approaches are generally developed for broader recommendation domains or rely on computationally intensive models. Therefore, this study proposes an attribute-based explainable recommendation system that provides transparent explanations based on culinary attributes while maintaining a lightweight recommendation process suitable for culinary tourism applications.

METHOD

Research Design

This study employed a system development approach to design and implement an Explainable Content-Based Recommendation System for culinary tourism (Pressman & Maxim, 2020). The recommendation system aims to provide personalized culinary destination recommendations while presenting understandable explanations regarding the recommendation results. The overall research procedure consists of five stages: data collection, data preprocessing, recommendation model development, explanation generation, and system evaluation. The research workflow is illustrated in Figure 1.

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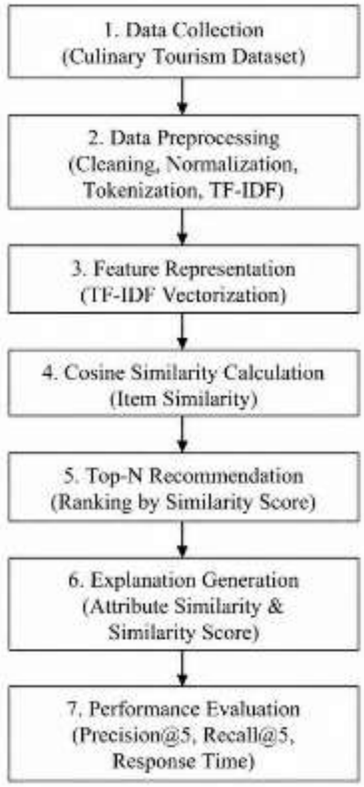

Figure 1. Research Framework

Proposed System Architecture

The proposed recommendation system consists of several interconnected modules. Initially, user preferences are processed by the Content-Based Filtering engine (Lops et al., 2022), while culinary destination descriptions are represented as TF-IDF vectors. Subsequently, the Cosine Similarity algorithm computes the similarity between user preferences and all available culinary destinations. Based on the similarity scores, the system generates the Top-*N* recommendations, and the explanation module produces interpretable reasons for each recommendation by highlighting shared culinary attributes(Tintarev & Masthoff, 2022). The overall architecture of the proposed system is illustrated in Figure 2.

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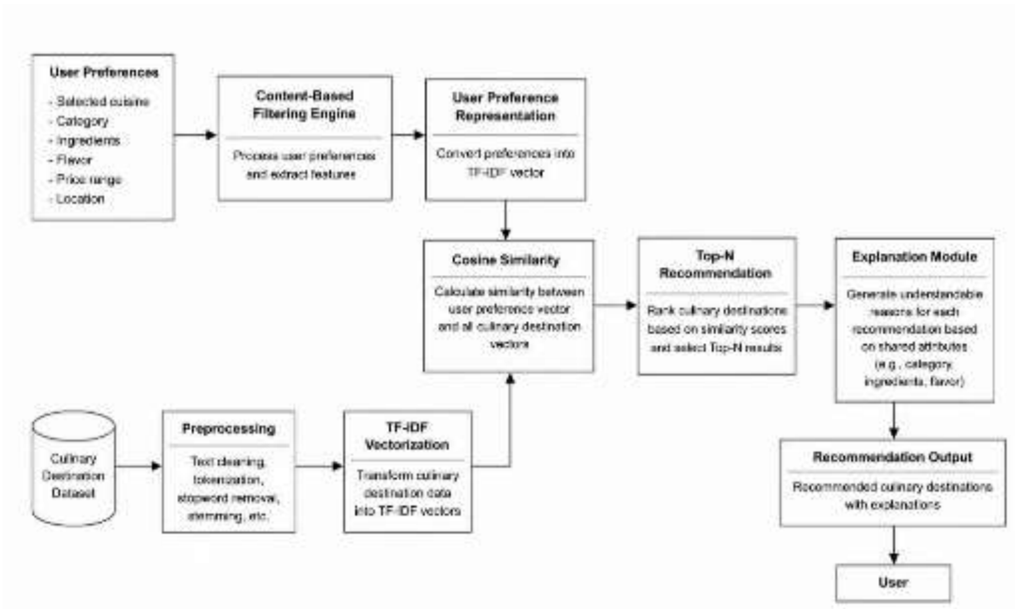

Figure 2. Proposed System Architecture

Culinary Dataset

The dataset used in this study consists of culinary tourism destinations collected from public tourism information sources and culinary directories in Palembang, Indonesia. Each culinary destination is represented by several descriptive attributes that characterize the destination. These attributes include the culinary category, primary ingredients, flavor characteristics, price range, service type, and geographical location. The use of descriptive item attributes enables the Content-Based Filtering approach to represent culinary destinations as feature vectors for similarity computation (Priskila et al., 2023).

Table 2. Dataset Characteristics

Description	Value
Culinary destinations	150
Food categories	8
Main ingredients	20
Flavor categories	6
Price categories	3
Districts	18

Each culinary destination is represented by several descriptive attributes, including culinary category, main ingredient, flavor, price range, location, and description. These attributes are transformed into feature vectors using the Term Frequency–Inverse Document Frequency (TF-IDF) technique, which assigns weights to important terms while reducing the influence of frequently occurring terms before similarity computation is performed using the Cosine Similarity algorithm (Christyawan et al., 2024).

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Table 3. Culinary Dataset Attributes

Attribute	Description
Culinary Name	Name of the culinary destination
Category	Traditional food, beverage, dessert, etc.
Main Ingredient	Fish, chicken, beef, vegetables, etc.
Flavor	Sweet, spicy, savory, sour
Price Range	Low, Medium, High
Location	District or tourism area
Description	Brief culinary description

Table 4. Sample Culinary Dataset

Culinary Name	Category	Main Ingredient	Flavor	Price	District
Pempek Candy	Traditional Food	Fish	Savory	Medium	Ilir Barat I
Mie Celor 26 Ilir	Noodle	Noodle	Savory	Medium	Ilir Barat I
Martabak HAR	Traditional Food	Egg	Savory	Low	Ilir Timur I
Es Kacang Merah Mamat	Dessert	Red Bean	Sweet	Low	Ilir Timur II
Pindang Musi Rawas	Traditional Food	Fish	Spicy	Medium	Seberang Ulu I

Data Preprocessing

Before generating recommendations, the collected dataset undergoes several preprocessing stages to improve recommendation quality. These stages include data cleaning, duplicate removal, missing value handling, text normalization, tokenization, stop-word removal, stemming, and TF-IDF vectorization, which are commonly applied in text mining and information retrieval to prepare textual data for feature extraction (Manning et al., 2008).

The Term Frequency–Inverse Document Frequency (TF-IDF) representation transforms textual information into numerical feature vectors by assigning higher weights to informative terms while reducing the influence of commonly occurring terms. This representation enables the recommendation model to measure the similarity among culinary destinations based on their descriptive characteristics before similarity computation is performed using the Cosine Similarity algorithm.

Recommendation Model

The Term Frequency–Inverse Document Frequency (TF-IDF) weighting method is used to measure the importance of a term in a culinary document relative to the entire dataset (Malikussaleh et al., 2025). The Term Frequency (TF) is calculated as follows:

$$TF(t,d) = \frac{f(t,d)}{\sum f(t,d)} \quad (1)$$

where:

$f(t, d)$= frequency of term *t* in document *d*.
$\sum f\ (t, d)$= total number of terms in document *d*.

The Inverse Document Frequency (IDF) is defined as

$$IDF(t) = \log(\frac{N}{df(t)}) \quad (2)$$

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where:

N= total number of culinary documents.
$df(t)$= number of documents containing term t.

The final TF-IDF weight is computed as

$$TFIDF(t,d) = TF(t,d) \times IDF(t) \qquad (3)$$

After obtaining the TF-IDF vectors, the similarity between two culinary destinations is calculated using Cosine Similarity. Similarity between culinary destinations is calculated using Cosine Similarity**.**

$$Similarity(A,B) = \frac{A \cdot B}{||A|| \times ||B||} \qquad (4)$$

where:

A represents the feature vector of the selected culinary destination.
B represents the feature vector of another culinary destination.
A·B denotes the dot product between vectors.
||A|| and ||B|| represent the Euclidean norms of each vector.

The similarity value ranges from 0 to 1. A higher value indicates greater similarity between culinary destinations. The similarity scores obtained from the Cosine Similarity computation are sorted in descending order. The system then selects the top-*N* culinary destinations with the highest similarity values. These destinations are presented to the user as personalized recommendations. Subsequently, the explanation module generates interpretable information by highlighting the shared culinary attributes associated with each recommendation, such as culinary category, main ingredient, flavor characteristics, price range, and location. The proposed recommendation model employs TF-IDF vectorization followed by Cosine Similarity to compute the similarity between culinary destinations. The TF-IDF representation is generated only once during the preprocessing stage, while the recommendation process calculates the similarity between the selected culinary destination and all available culinary destinations. Therefore, the computational complexity of the recommendation process is approximately O(n), where *n* represents the number of culinary destinations in the dataset. This lightweight computational approach makes the proposed recommendation system suitable for small- and medium-scale culinary tourism applications while maintaining acceptable response times.

Recommendation Evaluation Protocol

To evaluate the effectiveness of the proposed recommendation model, a recommendation evaluation protocol based on Precision@5 and Recall@5 was employed. Each of the 150 culinary destinations in the dataset was sequentially used as a query item, resulting in 150 evaluation queries, while the remaining culinary destinations served as candidate recommendations. For every query, the system generated the Top-5 recommendations using TF-IDF vectorization followed by cosine similarity ranking.

Since no publicly available ground-truth dataset exists for culinary tourism recommendation in this domain, relevance was operationally defined using the predefined culinary attributes adopted in this study, including culinary category, main ingredient, flavor characteristics, price range, and geographical location. A recommended culinary destination was considered relevant when it shared these predefined attributes with the query item. The same relevance criteria were consistently applied throughout all evaluation queries (Ricci et al., 2022).

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For each query, Precision@5 was calculated as the proportion of relevant culinary destinations among the five recommended items, while Recall@5 measured the proportion of relevant culinary destinations successfully retrieved from all relevant destinations defined by the adopted relevance criteria. The final Precision@5 and Recall@5 values reported in this study represent the arithmetic mean obtained across all 150 evaluation queries.
The evaluation metrics are defined as follows:

$$Precision@5 = \frac{|Rq \cap Recq|}{|Recq|} \quad (5)$$

$$Recall@5 = \frac{|Rq \cap Recq|}{|Rq|} \quad (6)$$

where $R_q$denotes the set of relevant culinary destinations for query q, and Rec_qdenotes the set of Top-5 recommendations generated by the proposed system.

Baseline Comparison

The proposed recommendation system extends the conventional content-based recommendation approach by integrating an attribute-based explanation module into the recommendation process. The explanation module operates as a post-processing component after recommendation ranking has been generated using TF-IDF vectorization and cosine similarity. Consequently, the recommendation ranking produced by the proposed system is identical to that of the standard TF-IDF–Cosine baseline, while the primary contribution of the proposed approach lies in improving the interpretability of recommendation results through natural language explanations derived from shared culinary attributes (Christyawan et al., 2024).

Unlike popularity-based recommendation methods, which recommend frequently selected items regardless of item characteristics, and conventional content-based recommendation methods, which only provide ranked recommendation lists, the proposed system explicitly communicates the shared culinary attributes underlying each recommendation. This enables users to understand why a culinary destination is recommended without modifying the underlying recommendation algorithm.
The functional comparison between the baseline recommendation approaches and the proposed system is presented in Table 5.

Table 5. Functional Comparison between Baseline Recommendation Approaches and the Proposed System

Feature	**Popularity-Based**	**Standard TF-IDF + Cosine**	**Proposed System**
Content-based recommendation	✗	✓	✓
TF-IDF feature representation	✗	✓	✓
Cosine similarity ranking	✗	✓	✓
Attribute-based explanation	✗	✗	✓
Natural language explanation	✗	✗	✓
Recommendation transparency	Low	Moderate	High
Recommendation interpretability	Low	Moderate	High

As shown in Table X, the proposed system preserves the recommendation capability of the standard TF-IDF–Cosine model while extending its functionality through an attribute-based explanation module. The

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explanation component does not alter the recommendation ranking; instead, it provides interpretable explanations describing the shared culinary attributes between the selected and recommended destinations. Therefore, the contribution of this study is not to improve recommendation accuracy but to enhance the interpretability and transparency of recommendation results within a lightweight content-based recommendation framework.

Explainable Recommendation Module

Unlike conventional recommendation systems that only present ranked recommendation lists, the proposed system provides attribute-based explanations for every recommended culinary destination. After generating the Top-N recommendations using TF-IDF vectorization and cosine similarity, the explanation module analyzes the descriptive attributes shared between the selected culinary destination and each recommended destination. Subsequently, the explanation module generates interpretable information by highlighting the shared culinary attributes associated with each recommendation, such as culinary category, main ingredient, flavor characteristics, price range, and location. These shared attributes are then transformed into natural language explanations to help users understand the reasons behind each recommendation (Tintarev & Masthoff, 2022).

For example, the system may generate the following explanation: “This destination is recommended because it belongs to the same culinary category, has similar main ingredients, shares comparable flavor characteristics, and falls within the same price range as the selected destination.” Unlike conventional recommendation systems that only present ranked recommendation lists, the proposed approach explicitly communicates the shared culinary attributes underlying each recommendation, thereby enhancing recommendation interpretability and helping users interpret the recommendation results.

System Implementation

The recommendation system was implemented as a web-based application. The recommendation engine was developed using Python, while the user interface was implemented using the Flask framework. Culinary information and user preference data were stored in a MySQL database. Users can search culinary destinations, view recommendation results, and read the explanation generated for each recommendation through the application interface.

Performance Evaluation

The proposed recommendation system was evaluated from two perspectives, namely recommendation quality and computational performance. Recommendation quality was measured using **Precision@5** and Recall@5 to determine the relevance of the generated recommendations Precision@5 measures the proportion of relevant culinary destinations among the top five recommendations, whereas Recall@5 measures the system's ability to retrieve relevant culinary destinations from the dataset. In addition, the average response time was measured to evaluate the computational efficiency of the recommendation process. The evaluation metrics used in this study are summarized in Table 6.

Table 6. Evaluation Metrics

Metric	Description
Precision@5	Measures the proportion of relevant recommendations among the top five recommended culinary destinations.
Recall@5	Measures the ability of the system to retrieve relevant culinary destinations from the dataset.
Response Time	Measures the average time required by the system to generate recommendation results.

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RESULT

System Implementation

The proposed Explainable Content-Based Recommendation System was successfully implemented as a web-based application using Python, Flask, and MySQL. The system enables users to search culinary destinations based on their preferences and receive personalized recommendations accompanied by understandable explanations. The recommendation process consists of user preference input, feature extraction using TF-IDF, similarity computation using Cosine Similarity, and explanation generation based on shared culinary attributes.

Figure 3 illustrates the main interface of the developed recommendation system. The interface provides users with an intuitive environment to search culinary destinations and view recommendation results.

Figure 3. Main Interface of the Proposed Recommendation System

After selecting a culinary destination, the system calculates the similarity score between the selected item and all culinary destinations stored in the dataset. The recommendation results are ranked based on the cosine similarity score, while the explanation module presents the shared culinary attributes associated with each recommendation. Figure 4 and 5 presents an example of the recommendation results generated by the proposed system.

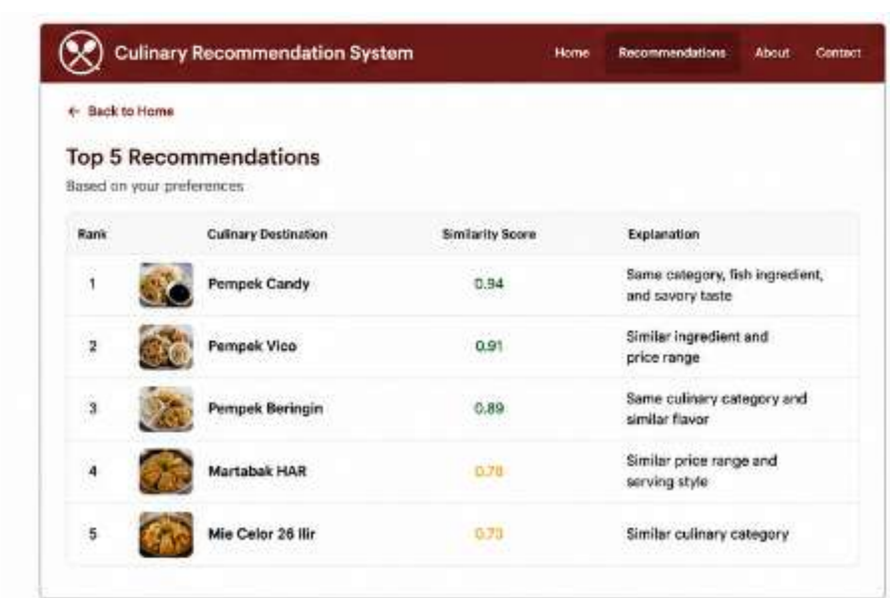

Figure 4. Recommendation Results with Explanation

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Figure 5. Example of Explanation Details

Recommendation Resulth

The recommendation engine generates personalized culinary recommendations by ranking culinary destinations according to their cosine similarity scores. Higher similarity values indicate greater similarity between the selected culinary destination and the recommended culinary destinations. In addition to the similarity score, the proposed system provides explanations describing the attributes that contribute to the recommendation.

Table 7. Example of Recommendation Results with Shared Culinary Attributes

Rank	**Culinary Destination**	**Similarity Score**	**Shared Culinary Attributes**	**Generated Explanation**
1	Pempek Candy	0.94	Category, Main Ingredient, Flavor	Recommended because it shares the same culinary category, fish ingredient, and savory flavor.
2	Pempek Vico	0.91	Main Ingredient, Price Range	Recommended because it has similar ingredients and belongs to the same price range.
3	Pempek Beringin	0.89	Category, Flavor	Recommended because it belongs to the same culinary category and has a similar flavor profile.
4	Martabak HAR	0.78	Price Range	Recommended because it falls within the same price range.
5	Mie Celor 26 Ilir	0.73	Category	Recommended because it belongs to the same culinary category.

Table 6 shows that the recommendation engine ranks culinary destinations according to their cosine similarity scores. In addition to the ranking results, the proposed system presents the shared culinary attributes identified between the selected and recommended destinations. These shared attributes are

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subsequently transformed into natural language explanations, enabling users to understand the basis of each recommendation without modifying the underlying recommendation algorithm.

Performance Evaluation Result

The recommendation system was evaluated using Precision@5, Recall@5, and average response time. Precision@5 measures the proportion of relevant recommendations among the top five recommendations, whereas Recall@5 evaluates the system's ability to retrieve relevant culinary destinations. Response time measures the computational efficiency of the recommendation process.

Table 8. Performance Evaluation Results

Evaluation Metric	Result
Precision@5	0.92
Recall@5	0.88
Response Time	0.73 s

The evaluation results indicate that the proposed recommendation system achieved a Precision@5 of 0.92, a Recall@5 of 0.88, and an average response time of 0.73 seconds. These results demonstrate that the recommendation engine is capable of producing relevant recommendations while maintaining efficient processing time suitable for real-time web-based applications.

Explanation Generation Results

One of the main contributions of this study is the integration of an explanation module into the recommendation process. Instead of presenting only a ranked recommendation list, the proposed system provides explanations describing the shared culinary attributes underlying each recommendation. An example of the generated explanation is as follows: "This culinary destination is recommended because it belongs to the same culinary category, uses similar main ingredients, and has a comparable savory flavor." The cosine similarity score of 0.94 is presented separately to indicate the degree of similarity between the selected and recommended destinations. The generated explanations enable users to understand the reasoning behind each recommendation, thereby enhancing the interpretability of recommendation results and supporting informed decision-making during culinary destination selection.

DISCUSSIONS

The proposed attribute-based explainable recommendation system successfully generates relevant culinary recommendations while supporting a more transparent recommendation process. Unlike conventional content-based recommendation systems that only present ranked recommendation lists, the proposed system provides explanations based on shared culinary attributes, including culinary category, main ingredient, flavor characteristics, price range, and location. These explanations enable users to understand why a particular culinary destination is recommended without modifying the underlying recommendation algorithm.

The recommendation performance is supported by the combination of TF-IDF vectorization and cosine similarity. TF-IDF effectively represents textual descriptions of culinary destinations, whereas cosine similarity measures the similarity between culinary feature vectors. The explanation module operates after the recommendation process by identifying shared descriptive attributes between the selected and recommended culinary destinations. Consequently, the proposed approach maintains computational efficiency while improving the interpretability of recommendation results.

The generated explanations are intentionally simple and attribute-oriented. Rather than presenting only similarity scores, the system explicitly communicates the common culinary characteristics shared by the recommended destinations. This attribute-based explanation assists users in interpreting recommendation

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results and increases the transparency of the recommendation process, particularly in culinary tourism where users frequently consider food category, ingredients, flavor, and price before making dining decisions.

Although the proposed system supports recommendation transparency, the explanation mechanism is currently based on attribute matching and predefined natural language templates. The system does not quantify the contribution of individual attributes to the similarity score or incorporate contextual factors such as user location, temporal preferences, or popularity. Future research may investigate more advanced explainable recommendation techniques while preserving the lightweight characteristics of the proposed system.

The proposed explanation module focuses on generating attribute-based explanations derived from shared culinary attributes rather than evaluating explanation effectiveness through user-centered experiments. The objective of this study is to demonstrate the feasibility of integrating lightweight explainable recommendations into a content-based culinary tourism recommendation framework. Therefore, the effectiveness of the generated explanations in terms of user trust, transparency, usefulness, and satisfaction was not evaluated in the current study.

CONCLUSION

This study proposed an attribute-based explainable recommendation system for culinary tourism that combines recommendation accuracy with transparent recommendation explanations. The proposed system employs TF-IDF vectorization to represent culinary destination characteristics and cosine similarity to identify relevant culinary destinations based on their descriptive features. To improve recommendation transparency, an explanation module generates natural language explanations by identifying the shared culinary attributes between the selected and recommended destinations, including culinary category, main ingredient, flavor characteristics, price range, and location. Unlike conventional recommendation systems that only present ranked recommendation lists, the proposed approach enables users to better understand the reasons underlying each recommendation without modifying the underlying recommendation algorithm.

The experimental results demonstrate that the proposed system achieved satisfactory recommendation performance, obtaining a Precision@5 of 0.92, Recall@5 of 0.88, and an average response time of 0.73 seconds. These results indicate that the recommendation model is capable of generating relevant culinary recommendations while maintaining computational efficiency suitable for real-time web-based culinary tourism applications. Furthermore, the attribute-based explanation module supports recommendation transparency by presenting the shared culinary characteristics associated with each recommendation, thereby providing users with more interpretable recommendation results.

Overall, the proposed attribute-based explainable recommendation system offers a practical and lightweight solution for culinary tourism recommendation by integrating similarity-based recommendation with attribute-oriented explanations. The proposed approach demonstrates that transparent recommendation explanations can be incorporated into a conventional content-based recommendation framework without introducing substantial computational overhead. Future research may extend the proposed system by incorporating contextual information, user feedback, or hybrid recommendation techniques to further improve recommendation quality and personalization while preserving recommendation transparency.

Future research will investigate the quality of the generated explanations through user-centered evaluation involving metrics such as explanation transparency, usefulness, trust, satisfaction, and perceived recommendation quality. In addition, comparative evaluation with alternative explanation techniques will be conducted to further validate the effectiveness of the proposed attribute-based explanation approach.

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