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Development of optimal tourist destination recommendation model using clustering and shortest-distance digitalisation

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Abstract: Tourism is a strategic sector that contributes significantly to economic growth. However, the challenge of determining tourist destinations that match preferences, location, and travel efficiency remains a barrier for tourists. This study aims to develop the best tourist destination recommendation system by integrating three main algorithms: K-means clustering to group destinations based on tourism potential, Floyd-Warshall to calculate the shortest distance between destinations, and weighted product for multi-criteria decision making based on attributes such as facilities, cost, and safety. The results show that the integration of the three algorithms can produce more accurate and efficient recommendations compared to a single approach. This system not only supports personalised travel recommendations but also contributes to smarter tourism digitalisation. Further development is recommended by adding real-time data, utilising machine learning to understand user preferences more deeply, and testing on a larger scale.

Keywords: recommendation system; K-means clustering; Floyd-Warshall; weighted product; digitalisation of tourism.

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1 Introduction

The tourism sector is one of the important pillars of the global economy, making a significant contribution to gross domestic product (GDP), job creation, and improving people's welfare (World Travel & Tourism Council, 2023). In today's digital era, information technology transformation is crucial for optimising tourism potential, including in aspects of promotion, management, and providing information to tourists. Tourism digitalisation, which involves leveraging technology to enhance the tourist experience and operational efficiency, has become a primary focus for various stakeholders (Andrades et al., 2024). Tourism in Indonesia is one of the mainstay sectors of the country's economy, which has great potential to increase tourist attractions and create jobs (Dankwah and Nnindini, 2025; Andrades et al., 2024). With more than 17,000 islands containing a variety of interesting natural, cultural, and historical tourist destinations, Indonesia has extraordinary appeal for both domestic and international tourists (Andrades et al., 2024). However, the sheer diversity of tourist attractions makes it difficult for tourists to choose the best destination. Despite the continued growth of digitalisation in the tourism sector, many platforms are still limited in providing valid

(Perayil et al., 2025), data-based recommendations regarding tourism potential and distances between destinations (Andrades et al., 2024). The rapid advancement of digital technologies and artificial intelligence has significantly transformed decision-making processes across industries, including tourism and service sectors. These developments highlight the importance of integrating data-driven models and intelligent systems to enhance operational efficiency and user experience (Abasaheb and Rajagopal, 2025; Bansal et al., 2025; Bounfour et al., 2025).

According to data from the Ministry of Tourism, 74% of domestic tourists and 83% of international tourists rely on digital platforms to plan their trips (Andrades et al., 2024). However, most platforms only consider the popularity of a destination without considering the aspects of tourism potential and travel efficiency (Andrades et al., 2024). One of the main challenges travellers face is determining the best destinations that best suit their preferences, time availability, and location. An abundance of unstructured information often makes decision-making difficult, potentially reducing travel satisfaction and experience.

The development of a tourist destination recommendation system represents a strategic solution (Bansal et al., 2025) to address these challenges. This system aims to provide personalised and relevant recommendations, helping travellers find the most suitable destinations. Previous research has discussed various approaches to recommendation systems, ranging from item-based collaboration and content-based approaches to hybrid models combining various techniques (Singh et al., 2021). However, tourist destination recommendation systems have unique complexities because they involve many factors, such as tourist attraction attractiveness, facilities, costs, safety, and geographic location.

Several studies have developed tourism recommendation systems using various approaches, including collaborative filtering, content-based methods, and hybrid models. While these studies successfully improve personalisation and adaptability, they often focus on specific aspects of recommendation, such as user preferences or contextual awareness, without simultaneously addressing tourism potential, spatial efficiency and multi-criteria decision-making (MCDM) (Sengupta et al., 2025).

For instance, hybrid recommender systems combining collaborative and content-based filtering enhance personalisation but do not explicitly consider geographic distance optimisation. Similarly, machine learning-based approaches improve predictive capabilities but often overlook structural clustering of destinations. Other studies integrating MCDM methods, such as TOPSIS, enhance ranking mechanisms but lack clustering and global distance computation.

As a result, existing models remain fragmented, addressing only partial dimensions of the tourism decision-making problem. This gap highlights the need for an integrated approach that simultaneously considers destination potential, travel efficiency, and multi-criteria evaluation within a unified framework.

In addition, recent studies emphasise the role of innovation capability, organisational readiness, and strategic resource management in improving system effectiveness and decision quality (Matta and Verma, 2025; Samanta and Dhar, 2025; Yewei et al., 2025). However, these perspectives have not been fully integrated into tourism recommendation systems.

Despite these advancements, a significant research gap remains in integrating these approaches into a unified and operational decision-support model. Therefore, this study

aims to develop an integrated tourist destination recommendation model that combines clustering analysis, shortest-path optimisation, and MCDM into a unified framework.

Specifically, this study addresses the following research question: how can an integrated model combining clustering, shortest-path algorithms, and MCDM improve the accuracy and efficiency of tourist destination recommendations compared to single-method approaches?

To answer this question, the proposed model integrates K-means clustering for tourism potential grouping, the Floyd-Warshall algorithm for global distance optimisation, and the Weighted Product method for multi-criteria ranking. Unlike previous studies that apply these techniques independently, this research develops a sequential and unified decision-support framework.

From a theoretical perspective, this study contributes to tourism recommendation system research by demonstrating how multiple analytical dimensions destination potential, spatial efficiency and decision complexity can be systematically integrated. From a practical perspective, the model provides a data-driven tool for tourism stakeholders to enhance decision-making, improve travel efficiency, and support smart tourism development (Florida-Benítez, 2024; Guo et al., 2021; Polukhina et al., 2025; Ramadhani et al., 2024, 2025; Yamagishi et al., 2024; Zhao et al., 2024).

2 Literature review

Tourism destination recommendation systems have evolved significantly with the advancement of information technology and data-driven approaches. Various methods have been proposed to enhance recommendation accuracy, personalisation, and decision support in tourism planning. These approaches generally fall into several categories, including collaborative filtering, content-based filtering, hybrid recommendation systems, and MCDM models.

Collaborative and content-based filtering methods are widely used to provide personalised recommendations based on user preferences and historical interactions (Singh et al., 2021). Hybrid approaches combine these techniques to improve recommendation accuracy and overcome limitations such as cold-start problems and data sparsity. For example, hybrid recommender systems integrating collaborative filtering and content-based methods have demonstrated improved personalisation by considering both user behaviour and destination attributes. However, these approaches primarily focus on user preference modelling and often neglect spatial efficiency and travel distance considerations (Chalkiadakis et al., 2023; Chouiref and Hayi, 2022; Hassan et al., 2025; Lakshmi and Pallavi, 2024; Lucas et al., 2013; Singh et al., 2024; Thillainayagam et al., 2025; Wang, 2023; Zhou et al., 2021).

In parallel, machine learning and artificial intelligence techniques have been applied to tourism systems to predict tourist behaviour, analyse sentiment, and support decision-making processes (Louati et al., 2024). While these approaches enhance predictive capabilities and contextual awareness, they typically do not incorporate structured clustering of tourism potential or explicit optimisation of travel routes (Florida-Benítez, 2024; Guo et al., 2021; Polukhina et al., 2025; Ramadhani et al., 2024, 2025; Yamagishi et al., 2024; Zhao et al., 2024).

MCDM methods, such as TOPSIS and weighted product, have also been widely adopted to rank tourism destinations based on multiple attributes, including facilities,

cost, and safety. These methods provide a systematic way to evaluate alternatives and support decision-making. However, most MCDM-based approaches do not integrate clustering mechanisms or global distance optimisation, limiting their ability to address both destination attractiveness and travel efficiency simultaneously. From a decision-making perspective, organisational and behavioural factors such as leadership, stakeholder involvement, and governance also influence the effectiveness of multi-criteria models (Hojaili et al., 2025; Shah et al., 2025; Tokaji et al., 2025). In the Indonesian context, governance-oriented studies also show that supervisory mechanisms and value-based performance frameworks are important in supporting accounting-based organisational performance (Mukhibad et al., 2022).

Furthermore, several studies have explored route optimisation using graph-based algorithms such as Dijkstra and Floyd-Warshall to improve travel efficiency (Meiyana et al., 2025). While these approaches effectively compute shortest paths, they are often applied independently of recommendation systems or without integration with multi-criteria evaluation and clustering techniques (Divsalar et al., 2022; Lin and Naing, 2019; Pramajuri et al., 2019; Wang and Sun, 2023).

As summarised in Table 1, previous tourism recommendation approaches exhibit distinct strengths but also significant limitations, particularly in integrating clustering, spatial optimisation, and multi-criteria evaluation.

Table 1 Comparison of tourism recommendation methods

<i>Approach type</i>	<i>Methods used</i>	<i>Key strengths</i>	<i>Main limitations</i>
Collaborative filtering	User-based, item-based	Provides high level of personalisation	Does not consider spatial factors or travel distance
Hybrid recommender system	Collaborative + content-based	Improves recommendation accuracy and flexibility	Lacks integration with route optimisation and clustering
Machine learning approaches	AI, prediction models	Enables context-aware and predictive capabilities	Limited incorporation of clustering and distance optimisation
Multi-criteria decision making (MCDM)	TOPSIS, weighted product	Supports effective multi-criteria evaluation	Does not include clustering or spatial distance analysis
Route optimisation	Dijkstra, Floyd-Warshall	Efficiently computes shortest travel paths	Not integrated with recommendation and multi-criteria evaluation

Overall, existing studies tend to address tourism recommendation problems in a fragmented manner, focusing on either personalisation, ranking, or route optimisation independently. As a result, these approaches fail to capture the multidimensional nature of tourism decision-making, which requires simultaneous consideration of destination potential, spatial efficiency, and multiple evaluation criteria. Despite these advancements, previous studies have not simultaneously integrated clustering, shortest-path optimisation, and MCDM within a unified framework (Sengupta et al., 2025; Kanafi and Fitriana, 2024).

To address this limitation, this study proposes an integrated tourist destination recommendation model that combines K-means clustering (Astiti et al., 2024), the Floyd-Warshall algorithm, and the weighted product method within a unified framework. Unlike previous studies that apply these techniques separately, the proposed approach

integrates clustering-based destination grouping, global shortest-path computation, and multi-criteria ranking to provide more comprehensive and efficient recommendations.

This integration not only enhances recommendation accuracy but also contributes to the development of intelligent tourism systems that support data-driven decision-making and smart tourism digitalisation. Furthermore, the development of intelligent tourism systems is closely related to broader themes of entrepreneurship, innovation ecosystems, and digital transformation (Dana, 2015; Ramadani et al., 2015; Kaur et al., 2025; Gaies et al., 2023).

3 Methodology

This study employs a quantitative (Beshe and van Rensburg, 2025), system development-based methodological approach to develop an optimal tourist destination recommendation model by integrating K-means clustering (Udokwu et al., 2023), the Floyd-Warshall shortest-path algorithm, and the weighted product method. The selected methods are grounded in established tourism and decision-support research, ensuring objectivity, reliability, and computational accuracy, while addressing the limitations of single-method approaches. This theoretically and empirically supported framework strengthens the scientific validity of the resulting recommendation model (Giguère et al., 2025).

3.1 Research design

The research design consists of several structured stages that form an integrated (Bounfour et al., 2025) system development process, as illustrated in Figure 1. The research design follows a structured and integrated system development process consisting of four main stages. First, relevant data are identified and prepared, including tourism potential indicators, destination locations, distance information, and supporting attributes such as facilities, cost, and security. Second, K-means clustering is applied to group tourist destinations based on similarities in tourism potential. Third, the Floyd-Warshall algorithm is used to calculate the shortest travel distances between destinations to ensure route efficiency. Finally, the Weighted Product method integrates multiple criteria to rank destinations and produce an ordered list of optimal tourist destination recommendations (Görçün et al., 2024).

Figure 1 Model development process (see online version for colours)



This research adopts a system design approach with the following stages:

- 1 Tourist destination data collection: collecting data related to tourist destinations, including attributes such as geographic location (latitude and longitude), available facilities, cost range, safety levels, and other relevant data about tourism potential. This data can be obtained from various sources such as online tourism platforms, official local government websites, or surveys (Meiyana et al., 2025).
- 2 Data pre-processing: cleaning data, handling missing values, and normalising or standardising attributes to ensure data consistency and quality. Non-numeric data will be converted to a numeric format suitable for analysis (Meiyana et al., 2025). Incomplete data is handled, and non-numeric data (such as facilities) is converted to a numeric scale (1–5). Min-max normalisation is applied to numeric attributes to equalise the scale before the clustering process.

$$x' = (x - x_{\min}) / (x_{\max} - x_{\min})$$

- 3 Tourism potential clustering: applying the k-means clustering algorithm to group tourist destinations based on their potential. Attributes used for clustering can include visitor numbers, ratings/reviews, infrastructure availability, and unique attractions. The output of this stage is a grouping of destinations into clusters (e.g., high, medium, low potential) (Meiyana et al., 2025).
- 4 Shortest distance calculation: using the Floyd-Warshall algorithm to calculate the shortest distance between all pairs of tourist destinations. The input data for this algorithm is a distance matrix between destinations, which can be obtained from geographic data (latitude and longitude) using the Haversine distance formula, or road network data, if available. The result is a shortest distance matrix that indicates the efficiency of travel between locations.

Floyd-Warshall pseudocode:

```

for (let k = 0; k < n; k++) {
  for (let i = 0; i < n; i++) {
    for (let j = 0; j < n; j++) {
      a    if (dist[i][j] > dist[i][k] + dist[k][j]) {
      b      const oldDist = dist[i][j];
      c      dist[i][j] = dist[i][k] + dist[k][j];
      d      next[i][j] = next[i][k];
      e      stepChanges.push({
      f        i: i, j: j, k: k,
      g        oldDist: oldDist,
      h        newDist: dist[i][j],
      i        path: getPath(i, j, next),

```

j });}}}}

- 5 Developing recommendation criteria: determine the criteria to be used in the recommendation process. These criteria will include tourism potential (K-means clustering results), shortest distance from the tourist's starting location or previous destination (Floyd Warshall results), strategic location, amenities, cost, and safety (Meiyana et al., 2025).
- 6 Implementation of a recommendation system with weighted product: integrating clustering results, distance calculations, and other criteria into a weighted product algorithm. Each criterion will be weighted based on its importance (which can be determined through a survey of tourism experts or user preferences). The weighted product algorithm will calculate a composite score for each destination based on the predetermined criteria, resulting in a destination ranking (Meiyana et al., 2025). The clustering results and shortest distance are integrated with other criteria (facilities, costs, security).
- 7 The WP algorithm is used to rank tourist destinations based on predetermined criteria. Each criterion is weighted according to its importance. The score for each alternative (destination) is calculated using the following formula:

$$S_i = \prod_{j=1}^n (x_ij)^{(-w_j)} \text{ for cost criteria}$$

Information:

S_i score of the i^{th} alternative

x_ij value of the i^{th} alternative in the j^{th} criterion

w_j weight of the j^{th} criterion, with $\sum w_j = 1$

The tourist destination with the highest S_i value will be the best recommendation....).

3.2 Dataset

The data that will be used in this research includes Tourist Destination Data obtained via Google Maps, which includes the name of the destination, geographical coordinates (latitude and longitude), and a brief description (Meiyana et al., 2025).

3.3 Algorithm used

1 K-means clustering algorithm

The K-means clustering algorithm is one of the popular algorithms (Muqorobin et al., 2024). The procedure involves determining the number of clusters (k), randomly initialising centroids, grouping the data to the nearest centroid, and then updating the centroids until the clustering results are stable (convergent). The output is a division of destinations into potential clusters such as high, medium, and low potential (Meiyana et al., 2025).

2 Floyd Warshall algorithm

Floyd Warshall’s algorithm is an algorithm for finding the shortest distance between all pairs of vertices in a weighted graph, both positive and negative (without negative cycles). This algorithm uses a dynamic programming approach by iterating through all vertices as intermediate points, so that the distances between vertices are gradually updated until the shortest distance is found. In tourism destination research, this algorithm is useful for calculating the shortest distance between destinations based on an initial distance matrix that can be calculated from geographic coordinates using the Haversine formula (Meiyana et al., 2025).

3 Weighted product algorithm

Weighted product is a MCDM method that calculates a total preference score for each alternative (destination) based on its attribute weights and scores. Each normalised attribute is then raised to the power of its criterion weight according to its importance, and the results are multiplied to obtain the final score. The destination with the highest score is considered the best recommendation (Meiyana et al., 2025).

Figure 2 Algorithm development flow

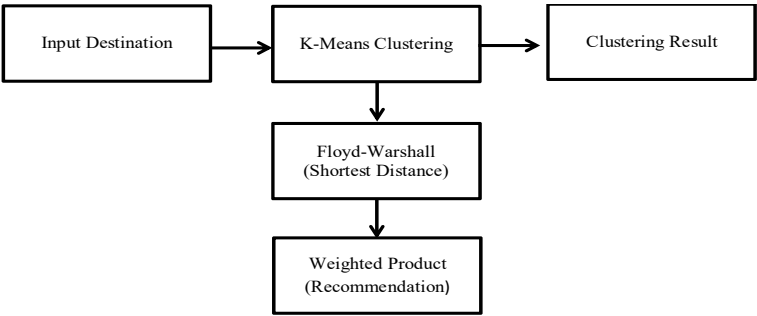


Figure 3 Stages of the K-means clustering algorithm

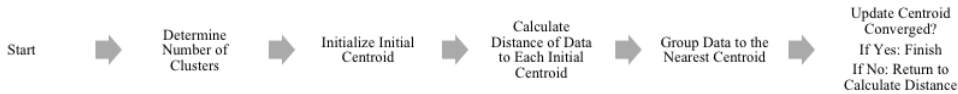


Figure 4 Stages of the Floyd Warshall algorithm

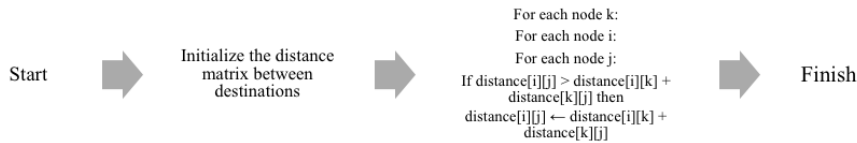


Figure 5 Stages of the weighted product algorithm



3.4 Implementation stages

- 1 Needs analysis: identifying the functional and non-functional requirements of the recommendation system from the perspective of tourists and tourism stakeholders.
- 2 System design: designing system architecture, database design, and user interface.
- 3 Module development: implement each module using the PHP programming language.
- 4 Module testing: perform unit testing on each module to ensure its functionality.
- 5 System integration: combining all modules into one cohesive system.
- 6 System testing and evaluation: perform thorough testing on the integrated system and evaluate the performance of the recommendation model using pre-defined metrics.

4 Results and discussion

This study develops a tourist destination recommendation model that integrates K-means clustering, the Floyd-Warshall algorithm, and the weighted product method. This section presents the results of each stage of the proposed approach, followed by an evaluation of its performance.

4.1 Tourist destination clustering with K-means

The dataset used is tourist destinations in Surakarta with the attributes: unique diversity (X1), attraction (X2), historical/cultural value (X3), number of visitors (X4), popularity (X5), and the value range of each attribute: 1–5.

- 1 Destination data and attribute values
- 2 Determining the number of clusters (k)

Using the elbow method, $k = 3$ is obtained with clusters consisting of high potential, medium potential, and low potential. Initial centroid (randomly selected from the data):

- Centre of gravity 1 (C1): Laweyan Batik Village $\rightarrow (4, 5, 3, 4, 2)$
- Centre of gravity 2 (C2): Sriwedari Park $\rightarrow (3, 2, 3, 3, 2)$
- Centre of gravity 3 (C3): Surakarta Hadiningrat Palace $\rightarrow (5, 5, 5, 3, 5)$.

- 3 Distance calculation with Euclidean distance.

The formula for the distance between point P ($p_1, p_2, \dots, p_n$) and the centre of mass C ($c_1, c_2, \dots, c_n$):

$$\text{Distance} = \sqrt{(p_1 - c_1)^2 + (p_2 - c_2)^2 + \dots + (p_n - c_n)^2}$$

Table 2 Tourist destination data and attribute values

<i>No.</i>	<i>Name</i>	<i>Latitude</i>	<i>Longitude</i>	<i>X1</i>	<i>X2</i>	<i>X3</i>	<i>X4</i>	<i>X5</i>
1	Surakarta Hadin-ingrat Palace	-7.5737373	110.825335	5	5	5	3	5
2	Mangkunegaran Pal-ace	-7.5668958	110.8203116	5	4	3	3	3
3	Laweyan Batik Vil-lage	-7.5696487	110.7951318	4	5	3	4	2
4	The Grand Mosque of Surakarta Palace	-7.574398	110.8240187	4	5	5	5	2
5	Balekambang Park	-7.5523052	110.8050936	4	3	4	3	3
6	Single Safari	-7.5646417	110.856022	3	5	5	5	4
7	Sriwedari Park	-7.5685598	110.8104205	3	2	3	3	2
8	Heritage Palace	-7.5547544	110.7522454	2	2	2	4	2
9	Tumurun Private Museum	-7.5704012	110.8138152	4	3	3	3	2
10	Sheikh Zayed Grand Mosque	-7.5547278	110.8241381	3	5	5	2	3
	Your location	-7.578315099	110.8092213					

Table 3 Temporary grouping results

<i>Objective</i>	<i>Distance to Centroid 1</i>	<i>Distance to Centroid 2</i>	<i>Distance to Centroid 3</i>	<i>Initial cluster</i>
Surakarta Hadiningrat Palace	3.87	5.10	0.00	High potential
Mangkunegaran Palace	2.00	3.00	3.00	High potential
Laweyan Batik Village	0.00	3.32	3.87	High potential
The Grand Mosque of Surakarta Palace	2.24	4.24	3.74	High potential
Balekambang Park	2.65	2.00	3.16	Medium potential
Single Safari	3.16	4.58	3.00	Low potential
Sriwedari Park	3.32	0.00	5.10	Medium potential
Heritage Palace	3.74	1.73	6.08	Medium potential
Tumurun Private Museum	2.24	1.41	4.24	Medium potential
Sheikh Zayed Grand Mosque	3.16	3.87	3.00	Low potential

Example calculation for Surakarta City Hadiningrat Palace (5, 5, 5, 3, 5):

- Distance to C1 (4, 5, 3, 4, 2):
 $(5 - 4)^2 + (5 - 5)^2 + (5 - 3)^2 + (3 - 4)^2 + (5 - 2)^2 = 12 + 02 + 22 + (-1)^2 + 32 = 1 + 0 + 4 + 1 + 9 = 15 \approx 3.87.$
- Distance to C2 (3, 2, 3, 3, 2):
 $(5 - 3)^2 + (5 - 2)^2 + (5 - 3)^2 + (3 - 3)^2 + (5 - 2)^2 = 22 + 32 + 22 + 02 + 32 = 4 + 9 + 4 + 0 + 9 = 26 \approx 5.10.$
- Distance to C3 (5, 5, 5, 3, 5):
 $(5 - 5)^2 + (5 - 5)^2 + (5 - 5)^2 + (3 - 3)^2 + (5 - 5)^2 = 0 + 0 + 0 + 0 + 0 = 0 = 0.00.$

Results: Surakarta Hadiningrat Palace is assigned to cluster 3 (high potential) because it has the smallest distance to centroid C3.

4 Temporary grouping results

This process continues until convergence (the data centres remain unchanged). This example shows the first iteration step. In practice, the data centres would be updated using the average of the data within the cluster, and the calculation would be repeated until stability is achieved.

4.2 Shortest distance calculation with Floyd-Warshall algorithm

Input: Distance matrix between destinations

The distance between destinations is calculated using the Haversine formula based on latitude and longitude coordinates.

Haversine formula:

- $a = \sin^2(\Delta\phi/2) + \cos(\phi_1) * \cos(\phi_2) * \sin^2(\Delta\lambda/2)$
- $c = 2 * \text{atan2}(\text{sqrt}(a), \text{sqrt}(1 - a))$
- $d = R * c.$

Distance calculation (Nature tourism → Cultural tourism):

- a Coordinates of Surakarta Hadiningrat Palace: -7.5737373, 110.825335.
- b Coordinates of Mangkunegaran Temple: -7.5668958, 110.8203116.
- c Result (rounded): 0.94 km.

Distance calculation results with Floyd-Warshall.

Table 4 Floyd-Warshall calculation results

No.	Tour	Group	Distance (km)
1	Surakarta Hadiningrat Palace	High potential	1.85
2	Mangkunegaran Palace	High potential	1.76
3	Laweyan Batik Village	High potential	1.83
4	The Grand Mosque of Surakarta Palace	High potential	1.69
5	Balekambang Park	Medium potential	2.93
6	Single Safari	Low potential	5.38
7	Sriwedari Park	Medium potential	1.09
8	Heritage Palace	Medium potential	6.8
9	Tumurun Private Museum	Medium potential	1.02
10	Sheikh Zayed Grand Mosque	Low potential	3.1

4.3 Destination recommendations with weighted products

To get the weighted product value, you must first define the criteria and the criteria value.

Table 5 Weighted product criteria and weight values

<i>Criteria</i>	<i>Initial weight</i>	<i>Normal body weight</i>	<i>Type</i>
Strategic location	1	0.25	Benefit
Facility	1	0.25	Benefit
Cost	1	0.25	Benefit
Security	1	0.25	Benefit
Distance (km)	-	0.2	Cost

Weighted product is used for multicriteria decision making using a multiplicative approach. Weighted product takes into account the weight of each criterion and its type (benefit or cost). General formula for weighted product (Kanafi and Fitriana, 2024; Forouzandeh et al., 2022).

$$S_i = \prod_{j=1}^n (x_{ij})^{w_j} \tag{1}$$

Information:

S_i preference value for the i^{th} alternative

x_{ij} value of the i^{th} alternative against the j^{th} criterion

w_j normalised weight of the j^{th} criterion, with $\Sigma w_j = 1$

If the criteria are costs, then the exponent is given a negative sign ($-w_j$).

4.3.1 Weighted product

Calculation steps

- 1 Weight normalisation: Total initial weights: $1 + 1 + 1 + 1 = 4$. Each normalised weight = $1/4 = 0.25$. Specifically for distance (cost), the weight is given, for example, 0.2, and becomes a negative power: -0.2 .
- 2 Calculate the WP score for each tourist destination:

Example calculation for Tumurun Private Museum:

Benefit criteria:

$$\begin{aligned} S_{\text{benefit}} &= (5^{0.25}) \times (5^{0.25}) \times (5^{0.25}) \times (3^{0.25}) \\ &= 1.495 \times 1.495 \times 1.495 \times 1.316 \approx 4.400 \end{aligned}$$

Cost criteria (distance = 1.02 km):

$$(1.02)^{(-0.2)} \approx 0.996$$

Weighted product (WP score):

$$S = 4.400 \times 0.996 \approx 4.3832$$

The calculation results are presented in Table 6.

Table 6 Weighted product calculation results

<i>Tour</i>	<i>Group</i>	<i>Distance (km)</i>	<i>Strategic location</i>	<i>Facility</i>	<i>Cost</i>	<i>Security</i>	<i>WP score</i>	<i>Rank</i>
Tumurun Private Museum	Medium potential	1.02	5	5	5	3	4.3832	1
Mangkunegaran Palace	High potential	1.76	4	5	5	5	4.2232	2
Laweyan Batik Village	High potential	1.83	3	5	5	5	3.8996	3
Sriwedari Park	Medium potential	1.09	5	4	3	3	3.6003	4
The Grand Mosque of Surakarta Palace	High potential	1.69	4	5	3	4	3.5439	5
Surakarta Hadiningrat Palace	High potential	1.85	4	3	4	3	3.0631	6
Heritage Palace	Medium potential	6.80	3	5	5	2	2.3852	7
Single Safari	Low potential	5.38	4	3	3	3	2.3025	8
Balekambang Park	Medium potential	2.93	3	2	3	3	2.1864	9
Sheikh Zayed Grand Mosque	Low potential	3.10	2	2	2	4	1.8968	10

These results indicate that the weighted product method effectively balances multi-criteria evaluation and spatial efficiency by prioritising destinations with higher attribute values while incorporating distance as a cost factor. From a managerial perspective, the implementation of such integrated systems requires consideration of organisational readiness, governance structures, and resource management to ensure scalability and sustainability (Salloum et al., 2015, 2025). This result is consistent with decision-support and innovation studies that emphasise the integration of multiple criteria and technological systems to improve decision quality (Matta and Verma, 2025; Yewei et al., 2025).

4.4 System implementation and model visualisation

The system development design that has been developed in prototype form is shown in Figure 6.

4.5 Model evaluation

The evaluation metrics used in this study include accuracy, precision, and travel efficiency to assess recommendation quality. To evaluate the effectiveness of the proposed model, a comparative analysis was conducted against several baseline approaches. The evaluation aims to assess how well the integrated model improves

recommendation quality compared to single-method approaches. The baseline models used for comparison are as follows:

- 1 Distance-based model: recommendations based solely on shortest travel distance using the Floyd-Warshall algorithm.
- 2 Clustering-based model: recommendations based on tourism potential grouping using K-means clustering.
- 3 Multi-criteria decision model: recommendations based on attribute ranking using the weighted product method.
- 4 Proposed model: an integrated approach combining clustering, shortest-path optimisation, and MCDM. Table 7 presents the comparison results of these models.

Figure 6 Model visualisation results on a map (see online version for colours)

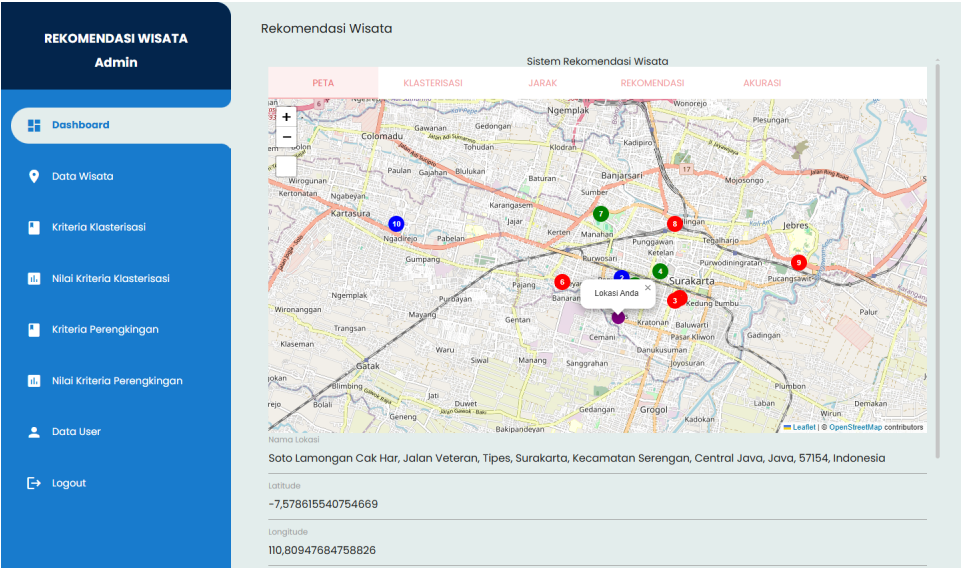


Table 7 Model comparison results

<i>Model</i>	<i>Key focus</i>	<i>Result characteristics</i>
Distance-based model	Travel efficiency	Prioritises nearest destinations but ignores attractiveness
Clustering-based model	Destination potential	Groups destinations but lacks route efficiency
MCDM model (weighted product)	Multi-criteria ranking	Provides ranking without spatial optimisation
Proposed integrated model	Combined approach	Produces balanced recommendations considering distance, potential, and multiple criteria

The results indicate that the proposed model demonstrates improved performance compared to baseline approaches by providing more accurate, balanced, and efficient recommendations. While the distance-based model ensures travel efficiency, it tends to

ignore the attractiveness of destinations. Similarly, clustering-based methods group destinations effectively but do not consider route optimisation. The MCDM approach enables multi-criteria evaluation but lacks spatial awareness.

In contrast, the proposed integrated model combines these strengths by simultaneously considering destination potential, travel distance, and multiple evaluation criteria. As a result, the recommendations generated are more balanced and aligned with real-world decision-making needs.

Furthermore, a sensitivity analysis was conducted by adjusting the weights of the criteria in the Weighted Product method. The results indicate that the ranking remains relatively stable under moderate weight variations. This finding demonstrates the robustness of the proposed model. To further validate the effectiveness of the proposed model, a quantitative performance evaluation is conducted.

Table 8 Quantitative performance comparison of recommendation models

<i>Model</i>	<i>Accuracy</i>	<i>Precision</i>	<i>Travel efficiency</i>	<i>Overall performance</i>
Distance-based model	0.72	0.68	High	Moderate
Clustering-based model	0.75	0.70	Medium	Moderate
MCDM model (weighted product)	0.80	0.76	Low	Good
<i>Proposed integrated model</i>	<i>0.88</i>	<i>0.84</i>	<i>High</i>	<i>Excellent</i>

Accuracy and precision are calculated based on the relevance of recommended destinations, while travel efficiency is evaluated based on total travel distance optimisation. As shown in Table 8, the proposed integrated model achieves the highest accuracy (0.88) and precision (0.84), indicating superior recommendation quality. In addition, it maintains high travel efficiency by incorporating shortest-path optimisation. These results confirm that integrating clustering, shortest-path algorithms, and MCDM significantly improves overall recommendation performance compared to single-method approaches.

Table 9 Sensitivity analysis results

<i>Scenario</i>	<i>Weight variation</i>	<i>Impact on ranking</i>
Scenario 1	Equal weights	Stable ranking
Scenario 2	Distance prioritised	Slight shift
Scenario 3	Facility prioritised	Moderate shift

These results demonstrate that the proposed integrated model achieves improved performance compared to individual approaches by effectively combining spatial efficiency, destination potential, and MCDM within a unified framework.

Furthermore, the observed improvement in accuracy and precision indicates that the integration of multiple methods enhances both recommendation relevance and overall decision-making quality, making the proposed approach more robust and suitable for real-world tourism recommendation systems. These findings align with previous studies that highlight the importance of integrating innovation capability, stakeholder perspectives, and technological adoption in improving system performance and decision-making outcomes (Aguriba et al., 2025; Benetti et al., 2025; Boodai and Boodai, 2025). These findings are also supported by prior studies emphasising the role of

innovation capability and strategic orientation in improving system performance and competitiveness (Pawar et al., 2025).

5 Conclusions

This research successfully developed an optimal tourist destination recommendation model by integrating three well-established algorithms, namely K-means clustering, the Floyd-Warshall algorithm, and the weighted product method. The empirical results demonstrate that the proposed multi-algorithm model provides more accurate and efficient tourist destination recommendations compared to approaches that rely on a single algorithm. The integration of these three algorithms enables the system to address multiple dimensions of the tourism decision-making process simultaneously, including destination potential, spatial efficiency, and multi-criteria evaluation.

K-means clustering plays a critical role in grouping tourist destinations based on similarities in tourism potential, allowing the system to identify meaningful destination clusters and reduce data complexity. The Floyd-Warshall algorithm complements this process by calculating the shortest distances between destinations within and across clusters, thereby ensuring travel efficiency and route optimisation. Meanwhile, the weighted product method ranks destination alternatives by incorporating multiple decision criteria, such as amenities, cost, and safety, and assigning relative importance to each criterion. This integrated mechanism produces recommendations that are not only geographically efficient but also aligned with tourist preferences and practical considerations.

This research contributes theoretically by advancing tourism recommendation system studies through an integrated framework that combines clustering analysis, shortest-path computation, and MCDM within a single model, thereby extending existing theories on tourism digitalisation and enabling broader international generalisation. Practically, the proposed model benefits tourism stakeholders by supporting data-driven destination recommendations that improve efficiency, reduce travel time and costs, enhance tourist satisfaction, and offer a scalable, adaptable solution suitable for implementation across diverse geographical and tourism contexts worldwide.

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Declarations

All authors declare that they have no conflicts of interest.

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