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SKYLINE QUERY BASED ON USER PREFERENCES IN CELLULAR ENVIRONMENTS

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Abstract— *The recommendation system is an important tool for providing personalized suggestions to users about products or services. However, previous research on individual recommendation systems using skyline queries has not considered the dynamic personal preferences of users. Therefore, this study aims to develop an individual recommendation model based on the current individual preferences and user location in a mobile environment. We propose an RFM (Recency, Frequency, Monetary) score-based algorithm to predict the current individual preferences of users. This research utilizes the skyline query method to recommend local cuisine that aligns with the individual preferences of users. The attributes used in selecting suitable local cuisine include individual preferences, price, and distance between the user and the local cuisine seller. The proposed algorithm has been implemented in the JALITA mobile-based Indonesian local cuisine recommendation system. The results effectively recommend local cuisine that matches the dynamic individual preferences and location of users. Based on the implementation results, individual recommendations are provided to mobile users anytime and anywhere they are located. In this study, three skyline objects are generated: soto betawi (C5), Mie Aceh Daging Goreng (C4), and Gado-gado betawi (C3), which are recommended local cuisine based on the current individual preferences (U_1) and user location (L_1). The implementation results are exemplified for one user located at (U_1L_1), providing recommendations for soto betawi (C5) with an individual preference score of 0.96, Mie Aceh Daging Goreng (C4) with an individual preference score of 0.93, and Gado-gado betawi (C3) with an individual preference score of 0.98. Thus, this research contributes to the field of individual recommendation systems by considering the dynamic user location and preferences.*

Keywords: *Individual Preference, Recommendation System, RFM Model, Skyline Query*

Intisari— *Sistem rekomendasi merupakan alat penting untuk memberikan saran yang dipersonalisasi kepada pengguna tentang produk atau layanan. Namun, penelitian sebelumnya mengenai sistem rekomendasi individu menggunakan skyline query belum mempertimbangkan preferensi individu pengguna yang dinamis. Oleh karena itu, tujuan penelitian ini adalah mengembangkan model rekomendasi individu yang berdasarkan keterkinian preferensi individu dan lokasi pengguna pada lingkungan seluler. Kami mengusulkan algoritma berbasis skor RFM (Recency, Frequency, Monetary) untuk memprediksi keterkinian preferensi individu pengguna. Penelitian ini, menggunakan metode skyline query untuk merekomendasikan kuliner lokal yang sesuai dengan preferensi individu pengguna. Atribut yang digunakan dalam memilih kuliner lokal yang sesuai adalah preferensi individu, harga, dan jarak antara pengguna dengan penjual kuliner lokal. Algoritma yang diusulkan telah diimplementasikan pada sistem rekomendasi kuliner lokal Indonesia berbasis mobile (JALITA). Hasilnya secara efektif merekomendasikan kuliner lokal yang sesuai dengan preferensi individu dan lokasi pengguna yang dinamis. Berdasarkan hasil implementasi, rekomendasi individu diberikan kepada pengguna seluler kapan pun dan di mana pun mereka berada. Pada penelitian ini, tiga objek skyline yang dihasilkan adalah soto betawi (C5), Mie Aceh Daging Goreng (C4), dan Gado-gado betawi (C3), merupakan kuliner lokal yang direkomendasikan berdasarkan keterkinian preferensi individu (U_1) da lokasi pengguna (L_1). Hasil implementasi dicontohkan pada salah satu pengguna, saat berada berada dilokasi (U_1L_1), memberikan rekomendasi kuliner lokal soto betawi (C5) dengan preferensi individu sebesar 0,96, Mie Aceh Daging Goreng (C4) dengan preferensi individu sebesar 0,93, dan Gado-gado betawi (C3) dengan preferensi individu sebesar 0,98. Dengan demikian, penelitian ini berkontribusi pada bidang sistem rekomendasi individu berbasis lokasi dan preferensi individu pengguna yang dinamis.*

Kata Kunci: *model RFM, preferensi individu, sistem rekomendasi, skyline query*

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INTRODUCTION

Mobile technology plays a vital role in transforming how individuals connect, interact, and share information in their daily lives. Mobile devices have become commonplace for communication and information exchange [1]. The advancements in mobile technology have prompted many companies to develop mobile-based services, resulting in improved outcomes [1]. The evolution of information technology has made it easier for users to access information anytime and anywhere through devices like mobile phones. However, limitations in screen size, memory, and network on these devices can sometimes slow down the search process [2].

Effective recommendation systems are valuable tools for users as they help them find products that align with their interests [3]. Recommendation systems are software that provide personalized product recommendations based on user data [3]. These systems have successfully addressed various challenges and offer several benefits to users, such as assisting in product selection, increasing sales transactions, and improving customer loyalty [3]. Given their advantages, recommendation systems have become increasingly important, especially for mobile users engaged in digital transactions [4]. Personalized recommendation systems rely on user perceptions of products or services to provide relevant suggestions [3].

One of the methods used in personalized recommendation systems is the skyline query [5]. This approach simplifies the process of selecting alternatives by filtering out non-dominating objects and retaining dominating objects for multi-criteria decision analysis [5]. Dominating objects are those that have no worse values than other objects in all dimensions and at least better values in one dimension [5]. The skyline query also allows for the filtering of uninteresting data by selecting a group of objects that dominate other objects in multidimensional data [5]. This method efficiently extracts objects with the best performance [5].

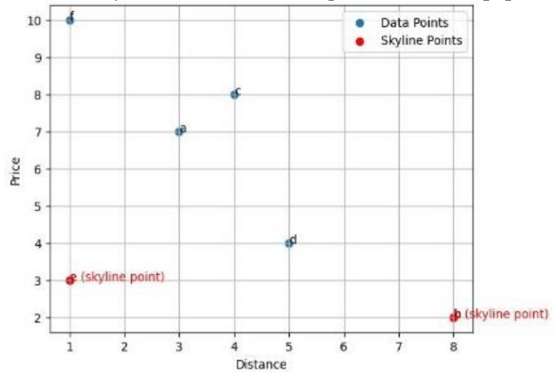

Figure 1. Skyline point

Utilizing personalized recommender systems can provide food recommendations based on user preferences [6]. However, the challenge lies in the fact that each user's preferences are distinct and change over time [7], thus necessitating their consideration. Alongside individual preferences, the user's location becomes a crucial attribute when generating recommendations based on personal preferences. Most recommendation systems for mobile users take user location into account. Typically, the nearest objects are selected as the most suitable options. Nevertheless, location-based recommendation systems encounter a challenge: the recommended objects may not align with the user's individual preferences. Food recommendation objects possess non-spatial attributes such as price and taste.

Given the aforementioned issues, conventional skyline queries are unable to address user needs. The development of a recommendation algorithm that can generate individual recommendations based on dynamic user preferences is essential. Numerous previous studies have proposed the development of recommendation systems using skyline queries to generate user-specific recommendations. Previous research in this domain has provided users with restaurant recommendations [8][9], albeit with predetermined user preferences. Studies have also been based on skyline queries [10], where user preferences are assumed to be constant fuzzy queries. Another study focused on business location recommendations [11], concentrating on desired nearby facilities but neglecting non-spatial attributes. Similarly, a different study [12] employed the GASKY algorithm to select appealing areas based on surrounding amenities without considering changing individual preferences. Progressing further, this research introduces a novel recommendation model centered on dynamic user preferences and locations.

In contrast to previous studies, this research advocates the development of a recommendation model predicated on dynamic user preferences and geographic data. A spatial-temporal analysis methodology is employed to ascertain the user's location over time. The proximity between the user and objects can be calculated based on the user's geographical coordinates. The recommendations provided are not constrained solely by the shortest distance between objects and the user; they also consider the alignment between individual user preferences and objects. Individual preferences can be identified through a temporal analysis of user transaction history data, taking into account factors such as recency, frequency, and monetary value for each user transaction.

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MATERIALS AND METHODS

This research involves several stages in the development of a personalized recommendation model that takes into account the latest individual preferences and user location. Figure 2 illustrates the steps involved in generating personalized recommendations. What sets this approach apart from previous studies is the utilization of the RFM method to determine the recency of dynamic individual user preferences.

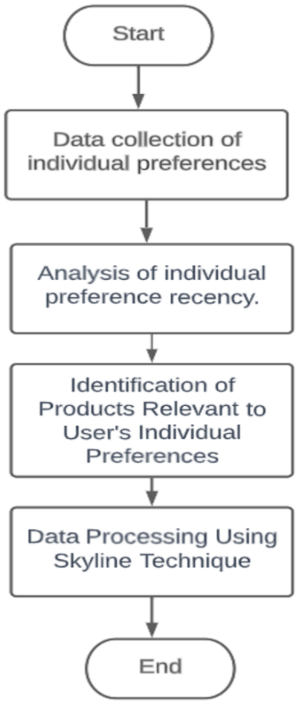

Figure 2. Stages of Individual Recommendation

1. Collecting Individual User Preference Data

To develop the individual recommendation model based on current individual preferences and user location, this study involves several stages. The JALITA (Jajanan Asli Nusantara Pintar) application is utilized as the data source for this research (https://jalita.giriwil.com). The JALITA application is a mobile-based local Indonesian culinary recommendation system that takes into account individual preferences and user location. Through the JALITA application, a significant amount of data has been collected. The application has a total of 357 registered users, and data from 147 transactions made by 24 users who have purchased local Indonesian cuisine have been successfully gathered. Additional data points are presented in Table 1.

Table 1. Data Sample

Data	Quantity	Description
Seller	235	Contains profile data of local culinary sellers from 22 regions in Indonesia
Local culinary menu	524	Contains local culinary profile data from 22 regions in Indonesia
User preferences	72	Contains user preference data from 22 regions in Indonesia

2. Dataset

In order to comprehend the individual preferences of users, the analysis of transaction datasets becomes highly significant. Several entities are employed to analyze transaction datasets, with a particular emphasis on key entities such as users, items, and transaction periods. The definition of each entity is as follows:

a. Transaction dataset (DB)
A structured collection of data that includes individual transactions involving various local cuisines within a specific period of time.

b. Users (U_i)
Customers who make purchases of local cuisines.

c. Items (I_k)
Local cuisines that are available for purchase or evaluation by users within the system.

d. Transaction period (t_i)
Indicates a specific time range during which transactions occur.

This study can examine individual user preferences for local cuisine based on changes or recency in user preferences, depending on the dataset used. The dataset is presented in Table 2.

Table 2. Transaction Dataset

userID	Transaction Date	Item	Total Price	Rating
U_1	2023-08-01 10:00	I_1	50.000	4
U_1	2023-08-05 15:00	I_2	30.000	3
U_1	2023-08-10 14:00	I_1	60.000	5
U_2	2023-08-05 16:00	I_1	40000	4
U_2	2023-08-20 11:00	I_2	20000	2
U_3	2023-08-10 12:00	I_2	25.000	3

Vectors are used to represent each user entity *(U_i)* and item entity *(I_k)*. Each element of the vector represents a specific feature of the user or item. Examples of features that can be included in the user representation vector are the total transaction value spent by the user, the number of transactions made, and the rating given by the user. Similarly, the item representation vector can include the number of purchases of the item, the total revenue generated from the item, and the average rating given by users to the item [13][14].

3. Analysis of Individual User Preferences based on RFM

In reality, each user has different preferences. The RFM analysis model was initially proposed by Hughes (1994) to segment major customers from large datasets based on three variables: recency, frequency, and monetary [15]. In the current digital era, understanding individual user preferences towards specific products or services is key to improving service quality and increasing customer loyalty [16]. This study combines several metrics that reflect customer behavior, such as purchase frequency, monetary value, recency of transactions, and customer ratings [17]. Individual user preferences are taken into account using these metrics :

a. Recency *(R)*

The user's most recent transaction for a single item during a specific time, is modeled :

$$R_{U_i I_k t_i} = T - max_{p \in t_i} t_{i,k,p} \quad (1)$$

$R_{U_i I_k t_i}$	:	The user's latest transaction *(U_i)* for an item *(I_k)* during a specific period *(t_i).*
$t_{i,k,p}$	:	The time of the user's transaction *(U_i)* for an item *(I_k)* during the period p, which is included within the period *(t_i)*
$max_{p \in t_i}$	:	The function that takes the maximum value of all transaction times that occur during the period *(t_i)*
T	:	current or end time of the period *(t_i)*

b. Frequency *(F)*

Transaction frequency by the user for a single item during a specific period is modeled:

$$F_{U_i I_k t_i} = \sum_{t \in t_i} x_{i,k,p} \quad (2)$$

$F_{U_i I_k t_i}$	:	Transaction frequency by the user *(U_i)* for a single item *(I_k)* during a specific period *(t_i)*
$x_{i,k,t}$	:	Indicator of user transactions *(U_i)* for item *(I_k)* at time *(t)* within the period *(t_i)*
$\sum_{t \in t_i}$		The summation of all transactions that occur during the period *(t_i)*

c. Monetary *(M):*

The total value of transactions spent by users for a single item during a specific period is modeled :

$$M_{U_i I_k t_i} = \sum_{p \in ti} m_{i,k,p} \quad (3)$$

$M_{U_i I_k t_i}$	:	The total value of transactions spent by users *(U_i)* for a single item *(I_k)* during a specific period *(t_i)*
$m_{i,k,p}$	:	The monetary value of transactions by the user *(U_i)* for an item *(I_k)* during the period *(p)* that falls within the period *(t_i)*
$\sum_{p \in ti}$	:	The summation of all transaction values that occur during the period *(t_i)*

d. Rating *(R_t)*

The evaluations provided by users for a single item during a specific period are modeled :

$$Rt_{U_i I_k t_i} = r_{i,k,\max(p \in t_i)} \quad (4)$$

$Rt_{U_i I_k t_i}$	:	The rating is given by the user *(U_i)* for an item *(I_k)* during the period *(t_i)*
$r_{i,k,p}$	:	The rating value is given by the user *(U_i)* for an item *(I_k)* during the period *(p)* that falls within the period *(t_i)*
$\max(p \in t_i)$	:	The function that retrieves the last transaction period within the period *(t_i)* in which the user provides a rating for an item *(I_k)*

Previous studies have used RFM values for customer segmentation based on their transactional behavior [18]. Research [19] predicted customer profitability dynamically over time based on their transaction history. Unlike previous research, this study develops an algorithm based on recency (R), frequency (F), and monetary (M) scores to predict products that align with the recency of individual user preferences. The pseudocode for this algorithm can be seen in Algorithm 1. The algorithm starts by reading the user's online purchase transaction dataset. The first process involves uploading the customer transactional dataset. The second process calculates the values of the R, F, and M attributes for each product the user purchases. The third process separates the three attributes, R-F-M, into five equal parts, each representing 20% of the total. These five parts are assigned scores of 5, 4, 3, 2, and 1 in

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descending order. The fourth process sums up the values of R, F, M, and rating to obtain the preference value (P). The formula to calculate the P value is shown in Equation (5).

$$P_{U_iI_kt_i} = ((F_{U_iI_kt_i} + M_{U_iI_kt_i}) - R_{U_iI_kt_i}) + Rt_{U_iI_kt_i} \quad (5)$$

The fifth process involves sorting the P values in descending order. The sixth process displays the P value with the highest (maximum) value.

Algorithm 1 Process of Preference with RFM
Input:
DB: Online retail dataset
Output:
P: preference
Algorithm steps:
1. Upload the customer transactional dataset
2. Compute the R, F, and M scores for each instance
3. Partition the three R–F–M attributes respectively into five equal parts, each equalizing 20% of all. The five elements are assigned 5, 4, 3, 2, and 1 scores by descent-dant order.
4. Compute P for each instance.
   P = ((F+M)-R)+ Rt
5. Sort the data of the P score by descendant order
6. Return P maximum

4. Determination of Relevant Products Based on Individual User Preferences

a. Distance between the User and Local Culinary Sellers

The distance between the user and local culinary sellers is a consideration in the recommendation selection process. The Global Positioning System (GPS) installed on mobile devices determines the user's and local culinary sellers' positions. The system can obtain latitude and longitude coordinates from both the user's and the local culinary sellers' positions. Based on this information, the distance between two points can be calculated using the latitude and longitude coordinates. Table 3 displays the notation used for this purpose.

Table 3. The notation used for distance calculation

Notation	Definition
$d_{(u,c)}$	distance between the user point and the culinary seller point
φ_1	Earth latitude coordinates (latitude) of the user point on Google Maps
φ_2	Earth latitude coordinates (latitude) of the culinary seller point on Google Maps
λ_1	Earth longitude coordinates (longitude) of the user point on Google Maps
λ_2	Earth longitude coordinates (longitude) of the seller point on Google Maps
r	Distance from users to traveling local food sellers

The Haversine formula calculates the distance between two points [20]. Based on this, the distance between the user and the local culinary seller can be calculated using Equation (6):

$$d_{(u,c)} = 2r.arcsin\left(sin^2\left(\frac{\varphi_2-\varphi_1}{2}\right) + \cos(\varphi_1).\cos(\varphi_2).sin^2\left(\frac{\lambda_2-\lambda_1}{2}\right)\right)^{1/2} \quad (6)$$

Once the user's location is known through GPS, the nearest local culinary sellers within a radius R can be determined. The distance between the user and the local culinary seller can be calculated using Equation (6). Figure 3 illustrates the positions of the user and the local culinary sellers within the radius R area.

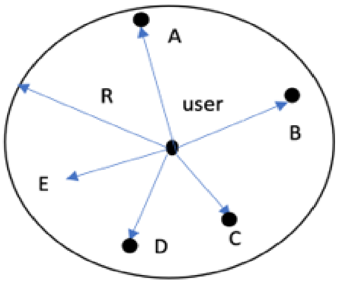

Figure 3. Illustration of User and Local Culinary Sellers' Positions within an R-Radius Area

b. Similarity between User Preferences and Local Culinary Options Available at User's Location

Every user has preferences that can be represented by a vector $P_u = (P_1, P_2, P_3, \dots, P_n)$, and culinary options have attributes $C_a = (C_1, C_2, C_3, \dots, C_n)$. Based on this, the similarity (S_u) between user preferences *(P_u)* and culinary options *(C_a)* can be calculated using the cosine similarity formula [21]. Mathematically, it can be written as Equation (7).

$$S_{(u,c)} = \frac{\sum_{i=1}^{n} PiCi}{\sqrt{\sum_{i=1}^{n} Pi^2} x \sqrt{\sum_{i=1}^{n} Ci^2}} \quad (7)$$

The similarity value between user preferences and available local culinary options at the user's location ranges from 0 to 1. A value of 1 indicates a high level of similarity, while a value of 0 indicates dissimilarity.

7. Data Processing using Skyline Query

Skyline query can extract interesting objects from multidimensional data based on user preferences [22]. It identifies interesting data objects from a given dataset [23]. The skyline query has the advantage of filtering out uninteresting data by selecting a set of points not dominated by others in the complex database [24]. Given a dataset (T) with dimensions (d), an object t1 dominates another object t2 if t1 has better values than t2 in every dimension and at least one dimension where it has a strictly better value. Better values can be either smaller or larger. The definition of domination is expressed in Equation (8):

$$\forall i = (1,2,\dots,d), t_1[i] \leq t_2[i], \\ \exists j = (1,2,\dots,d), t_1[j] < t[j] \quad (8)$$

RESULTS AND DISCUSSION

The cellular environment for generating individual preference recommendations comprises a database server, an application server, and two distinct groups of end users. As depicted in Figure 4, this cellular configuration operates within a cloud environment. It is assumed that both groups of end users engage with the application and database servers through a handshaking process to obtain authorization based on their respective roles. The first group of end users consists of sellers *(S_j)* offering various product items *(I_k)*. Each seller is situated at their current coordinates, specified by longitude *(S_jL_o)* and latitude *(S_jL_a)*. The second group comprises the end users *(U_i)* who will be the recipients of the recommendations. The historical transaction location and current location of each user are recorded, including their longitude *(U_iL_o)* and latitude *(U_iL_a)*.

The information pertaining to sellers *(S_j)*, product items *(I_k)*, and the location details of each seller, including their longitude *(S_jL_o)* and latitude *(S_jL_a)*, is stored in the database server. Additionally, the database server maintains the historical transaction records of the end user (U_i). It responds to requests from the business logic layer to retrieve or modify data. Whenever there are changes made by the end user, the database server updates the information in real time. Acting as an intermediary between the end user and the database server, the application server facilitates the handshaking process for authentication and authorization. This ensures that each end user can only access data and functionalities that are relevant to their role. Leveraging the data stored in the database server, the application server handles the business logic, including data processing and calculations.

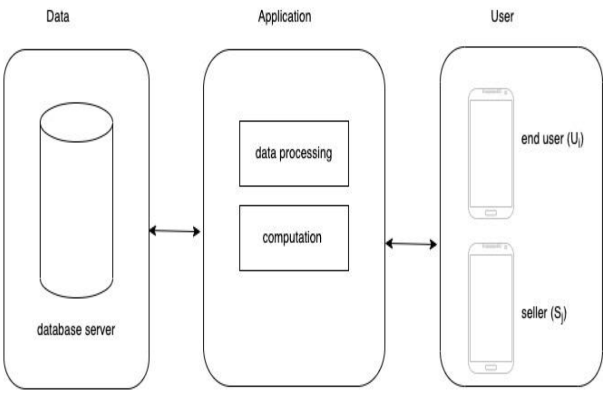

Figure 4. Cellular environment

User Location Analysis

Let's consider the user's location denoted as Lj, which can be represented as *L_j = (1, 2, 3,...,n)*. It is known that the user's current location *(L_1,U_1)* is situated in Taman Kencana, Bogor city, with the latitude coordinate *(U_1,L_a)* being -6.58712 and the longitude *(U_1,L_o)* being 106.8014. Additionally, Google Maps can provide information about local culinary sellers located within a maximum radius of 5 Km from the user. The details of these culinary sellers, stored in the database server, are presented in Table 4.

Table 4. Local culinary at the user's location

Culiner_ID	Culiner Name	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}
C1	Soto mie Bogor	2	4	2	4	3	3	3	3	3	3
C2	Asinan Bogor	3	3	3	3	4	4	3	4	4	3
C3	Gado-gado Betawi	4	3	3	3	2	4	3	4	4	4
C4	Mie Aceh Daging Goreng	3	4	1	2	2	4	5	5	5	5
C5	Soto Betawi	3	3	3	3	1	3	3	3	2	4

Analysis of Individual User Preferences

Each user's interaction with an item, particularly purchase transactions, is carefully documented. When a user *(U_1)* buys a specific item, this data is promptly stored in the user's client database. This guarantees that every purchase activity can be monitored and examined for the purpose of product recommendations. With this effective recording system in place, the system can gain a deeper understanding of customer preferences and behaviors. The interactions between the user *(U_1)* and various items *(I_k)* are presented in Table 5.

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Table 5. User's Individual Preferences

Culiner Name	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}
Mi Koclok	4	5	3	4	1	3	4	4	4	4
Nasi Lengko	4	5	4	3	1	4	4	5	4	4
Tahu Gejrot (C3) Empal Gentong	4	4	2	4	5	3	3	3	3	3
Daging	4	5	3	4	2	4	3	4	4	3
Empal Gentong Campur	4	5	3	4	2	4	3	4	4	3
Tahu Gejrot	4	2	4	3	5	4	4	5	3	3
Empal Asem Daging	4	5	3	4	4	4	4	4	3	4
Lontong	3	4	3	3	2	3	3	4	4	4
Empal Asem Campur	4	5	2	3	4	4	3	4	4	4
Nasi Jamblang	4	4	1	4	1	4	4	4	3	3
Nasi Jamblang	4	4	1	4	1	4	4	4	3	3

Analyzing Individual User Preferences with RFM

Using the online transaction history data of the customer *(U_1)*, an analysis was conducted to determine the individual user preferences. The transaction history of the customer is presented in Table 6. Algorithm 1 is employed to read and process the customer's transaction history.

Table 6. User Transaction History Data

Transaction code	Culiner_ID	Quantity	Transaction Date	Price	Total Price	Rating
TC1	MA2001	1	11/12/2021	52000	52000	5
TC1	MA2002	1	11/12/2021	52000	52000	5
TC1	MA2003	1	11/12/2021	52000	52000	5
TC1	MA2004	1	11/12/2021	52000	52000	5
.....	.....	.....	.....	.....	.....	.....
TC5	PM0003	5	11/12/2021	19300	96500	5

Once the transaction history data of the customer has been acquired, algorithm 1 can be utilized to calculate the recency *(R)*, frequency *(F)*, monetary *(M)*, and *P* values. Among these values, the highest P value will be considered as the benchmark for the individual user's preference.

Table 7. Calculation Result P

Culiner_ID	Recency	Frequency	Monetary	Rat	R	F	M	P
MA2001	3	2	104000	4	1	4	3	12
MA2002	3	2	97000	4	1	4	3	12
MA2003	3	2	82000	4	1	4	4	13
MA2004	3	3	88000	4	1	3	4	12
.....	.....	.....	.....	.....	.....	.....	.....	.....
PM0004	3	5	96500	5	1	3	4	13

Referring to Table 7, it is possible to identify two menus, namely Culiner_ID MA2003 and PM0004, which have the highest P values. Each local cuisine (C) possesses attributes (a) with distinct values for each attribute. These attributes collectively form a vector $a = (a_1, a_2, a_3, \ldots\ldots, a_n)$. The attributes associated with local cuisine can reflect the preferences of the user. Consequently, user preferences can be represented as $P = (p_1, p_2, p_3, \ldots\ldots, p_n)$. Subsequently, the menu with the highest value signifies the user preference based on their transactional data. In the event of multiple P values, it becomes necessary to calculate the average value for each preference using Equation (9).

$$P = \frac{\sum_{i=1}^{n} p_i}{number\ n} \quad \ldots\ldots (9)$$

To represent the user's preference value for the I-th attribute, let Pi be used, and let n denote the number of product values. Equation (3) is employed to calculate the preference value for each attribute, which falls within the range of 1 to 5. The calculation results of P for a user are presented in Table 8.

Table 8. Calculation Result P

Culiner_ID	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}
MA2003	4	2	4	3	5	4	4	5	3	3
PM0004	4	5	3	4	2	4	3	4	4	3
Value P	4	3.5	3.5	3.5	3.5	4	3.5	4.5	3.5	3

Calculating the distance between the user and the food vendors

Having knowledge of both the user and the local food vendors situated in close proximity to the user's current location is essential. For instance, suppose the user is presently located in Taman Kencana, Bogor city, with coordinates *(L_a,L_o)* = (-6.58712, 106.80141). Subsequently, Google Maps can furnish details regarding nearby food vendors within a maximum radius of 5 km from the user. The computed distances between the user and the food vendors in the user's location are presented in Table 9.

Table 9. Results of Distance Calculation

Seller_ID	Latitude	Longitude	Distance (Km)
BGR001	-6.590055	106.802869	0.36
BGR002	-6.574009	106.807499	1.60
BGR003	-6.583946	106.805780	0.59
BGR004	-6.587561	106.800335	0.12
BGR005	-6.590564	106.800130	0.40

By employing Equation (2), the calculation reveals that the distance between the user and the food vendor with the id_penjual BGR001 is 0.36 km. Likewise, the distances between the user and the food vendors BGR002, BGR003, BGR004, and BGR005 can be determined using the same approach.

Calculating the Similarity between User Preferences and Available Products in the User's Location

In the user's location, there are five local cuisines that are accessible. Subsequently, algorithm 2 is employed to carry out the process. The calculation results of the similarity between user preferences and the available products in the user's location, denoted as *S(u,c)*, are presented in Table 9.

Table 9. Calculation Result S(u,c)

Seller_ID	Culiner_ID	Culiner Name	$S_{(u,c)}$
BGR001	C1	Soto mie bogor	0.97
BGR002	C2	Asinan Bogor	0.99
BGR003	C3	Gado-gado Betawi	0.98
BGR004	C4	Mie Aceh Daging Goreng	0.93
BGR005	C5	Soto Betawi	0.96

Determining Skyline Objects Based on User Individual Preferences

During this stage, the algorithm examines the dataset (T) and the dimensions of the objects being recommended. The dataset containing the recommendation objects is displayed in Table 10.

Table 10. Object of Recommendation

ID_culinary	Distance	Preference	Price
C1	0.36	0.97	52000
C2	1.60	0.99	45000
C3	0.59	0.98	30000
C4	0.12	0.93	40000
C5	0.40	0.96	18000

The dataset provided in Table 10 requires normalization to standardize the attributes and bring them to a consistent scale. The normalized results of the dataset are displayed in Table 11.

Table 11. Normalization result

ID_culinary	Distance	Preference	Price
C1	0,36	0,97	1,00
C2	5,29	0,00	0,79
C3	0,59	0,98	0,35
C4	0,12	0,93	0,65
C5	0,40	0,96	0,00

Afterwards, the initial step involves arranging all records in ascending order by calculating the sum of their attribute values. These sorted records are then stored in the variable T'. The resulting dataset (T') after sorting based on the sum of each attribute is presented in Table 12.

Table 12. Dataset (T')

ID_culinary	Distance	Preference	Preference	total
C5	0,40	0,96	0,00	0,43
C4	0,12	0,93	0,65	0,78
C3	0,59	0,98	0,35	0,96
C1	0,36	0,97	1,00	1,43
C2	5,29	0,00	0,79	2,43

The second step involves storing the skyline objects in the variable S' and transferring the first record from T' to S. The third step entails comparing each record (t) in T' with all records in S as long as T' is not empty. If t is dominated by any record in S, it is removed from T', and the process is repeated for the next record. Conversely, if t dominates any record in S, it is transferred from T' to S, and the process is repeated for the subsequent record. The fourth step entails displaying the records stored in the variable S. The skyline query processing algorithm employed in this study utilizes the sort filter skyline (SFS) algorithm [25].

Algorithm 3 Process of sort filter skyline

Input:
T: dataset
d: dimensions
Output:
S: skyline
Algorithm steps:

1. Sort all records by the sum of all attributes in ascending get T'
2. Maintain a set S for skyline record. Move the first record into S from T'
3. While T' is not empty, for each record t in T': Compare t with all the records in S:
   - If t is dominated by some record in S, then remove from T' and continue the while loop with the next record;
   - Else, move from T' to S, do the whole loop with the next record
4. Return S

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According to Algorithm 3, the resulting output consists of culinary IDs C5, C4, and C3, which are considered skyline objects, while C1 and C2 are identified as dominated objects. Therefore, the recommended local cuisines for the user, taking into account the user's current individual preferences and location *(U_1L_1)*, are Soto Betawi (C5), Mie Aceh (C4), and Gado-gado Betawi (C3).

IMPLEMENTATION

The local culinary recommendation system proposed in this study leverages the services provided by Google Maps to determine the user's present location and identify nearby local culinary vendors. As depicted in Figure 5, the system consists of three key components: the user, the application server, and the database server. The process for users to receive recommendations for local culinary options is outlined as follows:

Step 1:
When the user launches the client application, the application sends a request to the GPS system to retrieve the user's current location information.

Step 2:
The GPS system furnishes the user's present location along with details regarding local cuisines offered by sellers situated within a 5 km radius of the user's location.

Step 3:
The client application sends data regarding the user's specific preferences to the application server.

Step 4:
The application server computes the user's personal preferences by analyzing their historical data stored on the database server. The calculations are conducted using Algorithm 1 to determine the highest P value among the recommended objects. Following that, each potential recommendation object is evaluated for its similarity to the user's individual preference (P) using Equation 3.

Step 5:
Once the attribute values of distance, price, and similarity for each recommended candidate object have been acquired, the application server proceeds to search for the skyline objects utilizing Algorithm 3.

Step 6:
The application server offers recommendations for local cuisine to the user, taking into account their location and personal preferences.

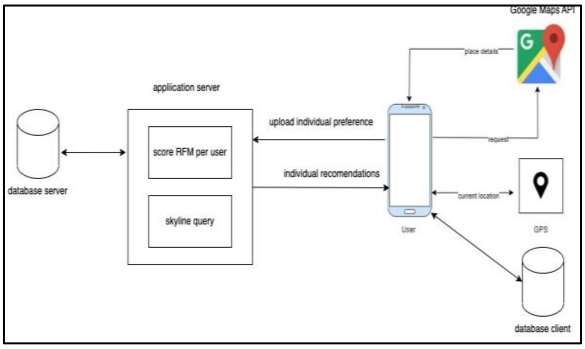

Figure 5. Local culinary recommendation system framework

When users are provided with local culinary recommendations that are tailored to their location and preferences, they can access the interface depicted in Figure 6. This interface showcases personalized recommendations for the user, presenting details such as the name of the local cuisine, individual preference scores, and the distance between the user and the seller. Users have the option to choose a recommendation by clicking on the desired item. Upon selection, the server records the user's purchase transaction.

Figure 6. Local culinary recommendation system interface

CONCLUSION

In this study, an RFM (Recency, Frequency, Monetary) algorithm is proposed for predicting individual user preferences, and the skyline query method is utilized to recommend local cuisine based on user preferences and location. The results demonstrate the success of this algorithm in recommending cuisine that aligns with individual preferences and the ever-changing user location.

During implementation testing, three skyline objects were generated: soto betawi, Mie Aceh Daging Goreng, and Gado-gado Betawi recommending local cuisine based on user preferences and the location at that time. The implementation results show that the recommendations for these culinary options are highly suitable for individual user preferences. Consequently, this research has effectively developed a location-based adaptive individual recommendation system.

Future research is expected to further develop a skyline query algorithm based on individual user preferences with streaming processing to enhance the accuracy and efficiency of individual recommendations. This will improve the responsiveness of the recommendation system and enhance the user experience in finding products that match their preferences. Thus, this research opens possibilities for a more advanced and adaptive recommendation system in the future.

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