

Integration Of Customer Preferences And Ordering Patterns For Menu Recommendation Personalization Using Topsis

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(Article Received: 17 October 2026; Article Revised: 21 November 2026; Article Published: 1 December 2026;)

ABSTRACT — Micro, Small, and Medium Enterprises (MSMEs) in the Indonesian culinary sector frequently face operational bottlenecks and customer decision fatigue during peak dining hours due to manual menu selection and conventional order-taking mechanisms. Preliminary field observations at Pondok Orange Restaurant in Pontianak revealed that customer menu deliberation required 6.5 to 8.2 minutes per table, while ordering queues extended up to 25 minutes during peak meal intervals. To address these operational challenges, this study designs and implements a web-based food menu recommender system utilizing the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The recommendation framework integrates two complementary data dimensions: Customer Preferences (incorporating menu selling price as a cost attribute and customer satisfaction ratings as a benefit attribute) and Operational Ordering Patterns (incorporating daily order frequency and real-time kitchen ingredient availability as benefit attributes). Developed using the Extreme Programming (XP) methodology on the Laravel framework, the system executes TOPSIS matrix computations with linear algorithmic complexity $O(m \times n)$ in under 5 ms without requiring extensive historical customer logs. Computational evaluation shows that Bubur Pedas achieved the highest preference score of 0.6498, securing the top recommendation ranking. Initial user acceptance testing with 30 dine-in patrons demonstrated strong alignment, yielding a Top-1 recommendation hit rate of 73.3%, a Top-3 hit rate of 90.0%, and an overall usability and relevance satisfaction score of 4.38 out of 5.00. Software verification via White-Box Testing (Statement Testing and Basis Path Testing, $V(G) = 4$) confirmed that all four independent algorithmic paths and mathematical boundary conditions executed successfully according to technical design specifications.

Keywords — Food Menu Recommendation; TOPSIS Algorithm; Customer Preferences; Ordering Patterns; White-Box Testing.

Integrasi Preferensi Pelanggan Dan Pola Pemesanan Untuk Personalisasi Rekomendasi Menu Menggunakan Topsis

ABSTRAK — Usaha Mikro, Kecil, dan Menengah (UMKM) pada sektor kuliner di Indonesia kerap menghadapi hambatan operasional dan kelelahan pengambilan keputusan (decision fatigue) oleh pelanggan saat jam sibuk akibat pemilihan menu secara manual dan pencatatan konvensional. Observasi lapangan awal pada Rumah Makan Pondok Orange di Kota Pontianak menunjukkan waktu pertimbangan memilih menu memerlukan 6,5 hingga 8,2 menit per meja dengan antrian mencapai 25 menit pada jam makan padat. Untuk mengatasi kendala operasional tersebut, penelitian ini merancang dan membangun sistem rekomendasi menu berbasis web menggunakan algoritma Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Kerangka rekomendasi mengintegrasikan dua dimensi data yang saling melengkapi: Preferensi Pelanggan (harga menu sebagai atribut biaya dan rating kepuasan sebagai atribut keuntungan) serta Pola Pemesanan Operasional (frekuensi pesanan harian dan ketersediaan stok bahan baku dapur secara real-time sebagai atribut keuntungan). Dikembangkan menggunakan metodologi Extreme Programming (XP) pada framework Laravel, sistem mengeksekusi komputasi matriks TOPSIS dengan kompleksitas linier $O(m \times n)$ di bawah 5 ms tanpa menuntut riwayat transaksi terdahulu dari pelanggan baru. Hasil evaluasi komputasi menunjukkan Bubur Pedas memperoleh skor preferensi tertinggi sebesar 0,6498 dan menempati peringkat pertama. Pengujian penerimaan awal bersama 30 pelanggan menunjukkan keselarasan yang tinggi, menghasilkan Top-1 hit rate sebesar 73,3%, Top-3 hit rate sebesar 90,0%, serta skor kepuasan relevansi 4,38 dari skala 5,00. Pengujian logika sistem melalui White-Box Testing (Statement Testing dan Basis Path Testing, $V(G) = 4$) membuktikan bahwa seluruh empat jalur independen dan kondisi batas komputasi berhasil dieksekusi sesuai spesifikasi teknis perancangan.

Kata Kunci — Sistem Rekomendasi Menu; Algoritma TOPSIS; Preferensi Pelanggan; Pola Pemesanan; White-Box Testing.

1. Introduction

The rapid evolution of information and communication technology in the modern digital era has triggered profound transformations across global commerce and the service industry [1]. Digital transformation has accelerated rapidly, compelling enterprises to adapt systematically and integrate

advanced computational technologies as core components of their business strategies [2]. In particular, the deployment of web-based applications represents a vital strategic initiative widely adopted by modern enterprises to optimize operational workflows, expand market reach, and significantly enrich customer service experiences [3], [4].

The Indonesian culinary sector has experienced sustained expansion, driven by surging consumer demand for swift, practical, and superior dining services. Nevertheless, many local culinary Micro, Small, and Medium Enterprises (MSMEs) continue to rely on manual order-taking and conventional paper-ledger accounting, resulting in transaction bottlenecks and extended customer queues during peak dining hours [5]. Pondok Orange Restaurant is a prominent culinary enterprise situated in Pontianak, West Kalimantan, that has traditionally operated using manual physical logbooks and cash-based settlements. The restaurant offers a wide assortment of regional specialty dishes, including bubur pedas (spicy porridge), mie sagu goreng (fried sago noodles), mie sagu rebus (boiled sago noodles), mie tiaw goreng, mie tiaw rebus, bubur nasi daging sapi (beef porridge), bubur nasi daging ayam (chicken porridge), pentol kuah, and indomie telur. Despite steady sales growth averaging 120 to 180 food portions served daily, the continued reliance on manual order processing introduces severe operational friction. Preliminary field observations conducted over a two-week period during peak lunch (11:30–13:30) and dinner (18:30–20:30) intervals revealed that customer menu deliberation required an average of 6.5 to 8.2 minutes per table due to decision fatigue when navigating the extensive, non-categorized physical menu. Consequently, cumulative queue wait times during peak hours stretched between 15 to 25 minutes before orders could be recorded. An initial pre-study survey administered to 45 dine-in patrons corroborated this operational constraint: 73.3% of respondents reported difficulty and hesitation in deciding what to order without personalized dish guidance, while 68.9% experienced frustration with service latency stemming from manual order recording and kitchen queuing. Furthermore, handwritten logbook orders resulted in an average transcription or communication error rate of 8.5% during peak meal shifts, triggering meal delivery discrepancies and food preparation delays. These quantitative findings demonstrate an urgent need for an automated, data-driven menu recommender system tailored to the operational realities of culinary MSMEs.

Recommender systems constitute an essential application of artificial intelligence developed to assist users in identifying optimal choices through structured data analytics and user preference modeling [6], [7]. In the food and dining sector, automated recommendation engines help patrons discover culinary choices aligned with individual taste preferences while streamlining the institutional decision-making process [8]. The primary objective of this research is to design and develop a web-based food menu recommender system for Pondok Orange

Restaurant utilizing the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The system assists customers in selecting dishes effectively based on personal preferences and empirical ordering patterns, thereby supporting restaurant operations in boosting service efficiency and customer satisfaction.

2. Literature Review

Food Menu Recommender Systems

Traditional recommender system architectures primarily implement *Collaborative Filtering* [9], *Content-Based Filtering* [10], or *Hybrid* methodologies [11]. While Collaborative Filtering is extensively adopted in commercial-scale platforms, it exhibits inherent limitations, including substantial matrix factorization computing costs and high vulnerability to the *cold-start* problem, wherein recommendations fail for newly registered users without historical transaction logs [24], [39]. Consequently, Multi-Criteria Decision Making (MCDM) methodologies have gained substantial prominence in dietary recommendation systems, as they enable deterministic, real-time evaluations across conflicting criteria without requiring extensive training datasets [12], [13].

TOPSIS Method

First formulated by Hwang and Yoon [14], the TOPSIS method remains one of the most robust MCDM algorithms in applied decision analysis [15], [16]. A key computational advantage of TOPSIS is its strictly linear algorithmic complexity $O(m \times n)$, where m represents the number of candidate alternatives and n denotes the evaluation criteria. This enables sub-5-millisecond server-side processing without demanding costly computational infrastructure [40]. Furthermore, TOPSIS geometrically identifies the optimal compromise alternative that simultaneously maintains the minimum Euclidean distance from the positive ideal solution (A^+) and the maximum Euclidean distance from the negative ideal solution (A^-) [17], [34]. This bidirectional evaluation provides superior stability compared to simple additive models (such as SAW) by heavily penalizing alternatives with severe deficits in critical criteria (e.g., out-of-stock items) despite favorable pricing. Prior studies have demonstrated TOPSIS efficacy in restaurant selection [18], product procurement [19], food menu recommendation [20], and hybrid AHP-TOPSIS integrations [21], [22].

Research Gap and System Novelty

A comprehensive review of existing literature highlights four prominent research gaps: (1) prevalence of single-perspective bias, which focuses exclusively on subjective consumer ratings [18], [25]

or historical sales volume [23], [26]; (2) persistent omission of kitchen operational logistics and real-time ingredient inventory; (3) absence of objective scale conversion frameworks for heterogeneous MSME transactional metrics; and (4) lack of rigorous software quality verification using *White-Box Testing* on recommendation algorithms [27], [28].

To resolve these shortcomings, this research introduces four core novelties: First, a Cross-Dimensional Integrated Decision Model that combines the Customer Preference Dimension (Price as a *cost* attribute and Satisfaction Rating as a *benefit* attribute) with the Operational Ordering Dimension (Order Popularity as a *benefit* attribute and Real-Time Kitchen Stock Availability as a *benefit* attribute). Second, a real-time, adaptive recommendation pipeline resistant to cold-start anomalies that executes calculations in < 5 ms. Third, an objective 1–5 Likert scale standardization framework tailored for heterogeneous MSME datasets. Fourth, rigorous verification of algorithmic logic via formal Statement Testing and Basis Path Testing achieving a 100% test execution pass rate.

3. Research Methods

System Development Method

System engineering followed the Extreme Programming (XP) framework, a highly adaptive methodology within Agile Software Development [29], [30]. XP was selected due to its flexibility in accommodating shifting stakeholder requirements and supporting rapid development iterations, making it optimal for MSME digital initiatives [31], [32]. The XP lifecycle comprised four stages: (1) *Planning*, identifying functional and non-functional requirements; (2) *Design*, formulating software architecture through Unified Modeling Language (UML) specifications; (3) *Coding*, constructing the web platform using PHP with the Laravel framework, HTML, CSS, and MySQL; and (4) *Testing*, executing structured White-Box Testing [33].

System Architecture and Process Flow

The food menu recommender architecture for Pondok Orange Restaurant follows the Model-View-Controller (MVC) pattern implemented in Laravel. This architecture cleanly decouples restaurant operational data (MySQL database) from customer presentation layers (blade views) and algorithmic logic (controller). The structural workflow is illustrated in Figure 1.

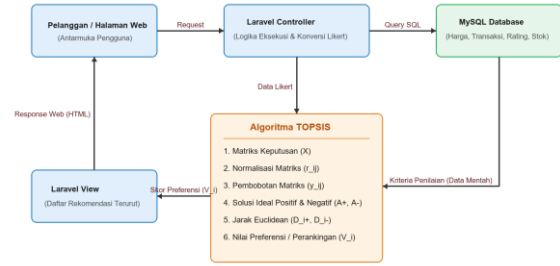


Figure 1. Architecture of TOPSIS-based menu recommendation process

The recommendation execution proceeds through three dynamic stages: (1) Input Data Ingestion: Upon customer access, the system queries the database to retrieve registered menu items, computes popularity metrics from order logs, fetches customer ratings, and verifies kitchen inventory levels; (2) Laravel Controller Execution: Raw metrics are converted to standardized 1–5 Likert scales, followed by sequential execution of TOPSIS matrix equations; (3) Dynamic Visualization: Evaluated preference scores V_i are sorted in descending order and dynamically presented on the responsive customer web interface.

Mathematical Formulation of TOPSIS Algorithm

TOPSIS serves as the core algorithm for ranking menu alternatives [14], [34]. The mathematical formulation is structured as follows:

Step 1: Constructing the Decision Matrix. The decision matrix X is established based on m candidate menu items evaluated across n criteria:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Step 2: Decision Matrix Normalization. Vector normalization is conducted using the Euclidean vector length formulation [36]:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (2)$$

Step 3: Weighted Normalized Matrix Calculation. The weighted normalized matrix is derived by multiplying normalized matrix elements by criterion weights w_j [37]:

$$y_{ij} = w_j \times r_{ij} \quad (3)$$

Step 4: Determining Ideal Solutions. The positive ideal solution (A^+) and negative ideal solution (A^-) are established based on criterion classification (benefit or cost):

$$A^+ = \{y_1^+, y_2^+, \dots, y_n^+\} \quad (4)$$

$$A^- = \{y_1^-, y_2^-, \dots, y_n^-\} \quad (5)$$

Step 5: Calculating Euclidean Distances. The Euclidean distance of each alternative from the positive ideal solution (D_i^+) and negative ideal solution (D_i^-) is computed as follows [38]:

$$D_i^+ = \sqrt{\sum_{j=1}^n (y_{ij} - y_j^+)^2} \quad (6)$$

$$D_i^- = \sqrt{\sum_{j=1}^n (y_{ij} - y_j^-)^2} \quad (7)$$

Step 6: Calculating Relative Closeness (Preference Score). The preference score (relative closeness) V_i determines the final recommendation hierarchy:

$$V_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (8)$$

Criteria Modeling and Weighting

Four distinct criteria were modeled to reflect both Customer Preferences (Price C_1 as a *cost* attribute and Rating C_3 as a *benefit* attribute) and Operational Ordering Patterns (Popularity C_2 as a *benefit* attribute and Kitchen Stock C_4 as a *benefit* attribute). Criteria definitions and weight allocations are summarized in Table 1.

Table 1. Definition of menu evaluation criteria

Code	Criterion	Dimension	Attribute	Weight
C1	Price	Preference	Cost	0.2000
C2	Popularity	Ordering Pattern	Benefit	0.3333
C3	Customer Rating	Preference	Benefit	0.2667
C4	Stock Availability	Ordering Pattern	Benefit	0.2000

The determination of criteria weights was established through a structured Focus Group Discussion (FGD) and expert judgment involving three key operational stakeholders at Pondok Orange Restaurant: the restaurant owner, the head chef (kitchen manager), and the lead cashier. A direct rating prioritization method was employed to reflect operational priorities and consumer dynamics. As detailed in Table 1, the highest weight was allocated to Order Popularity ($C_2 = 0.3333$ or 33.33%) because empirical daily sales volume and historical ordering patterns represent the strongest, most direct market validation of customer taste and dish viability in

daily operations. Customer Rating (C_3) was assigned the second-highest weight of 0.2667 (26.67%) to safeguard culinary quality and patron satisfaction, ensuring that highly rated dishes are actively promoted. Menu Selling Price (C_1) was assigned a weight of 0.2000 (20.00%) as a cost attribute, serving as an economic balancing parameter that accounts for customer price sensitivity. Kitchen Stock Availability (C_4) was allocated an equal weight of 0.2000 (20.00%) as an operational feasibility parameter to prevent the system from recommending dishes whose primary ingredients are depleted or critically constrained, thereby mitigating kitchen bottlenecks and order cancellations. The cumulative weight across all four criteria satisfies $\sum w_j = 1.0000$.

4. Results and Discussion

4.1. Results

Menu Assessment Data and Likert Scale Standardization

Evaluation data were compiled from operational database records encompassing ten representative menu items at Pondok Orange Restaurant. Standardizing multi-source metrics into a 1–5 Likert scale is necessary to align heterogeneous data dimensions (monetary values, portion sales, survey ratings, and inventory counts) into a uniform, objectively comparable domain. Price conversion thresholds (C_1) are detailed in Table 2.

Table 2. Conversion of menu selling price to Likert scale (C_1)

Likert Value	Price Range (IDR)	Category
1	> 30,000	Very Expensive
2	20,001 – 30,000	Expensive
3	15,001 – 20,000	Moderate
4	10,001 – 15,000	Affordable
5	≤ 10,000	Very Affordable

The conversion thresholds for menu selling price (C_1) in Table 2 were formulated based on the empirical price distribution of all 20 active menu items at Pondok Orange Restaurant, where prices range from IDR 8,000 to IDR 35,000. This range was partitioned into five operational quintile brackets reflecting local Pontianak consumer purchasing power: Likert 5 ($\leq$ IDR 10,000) corresponds to entry-level comfort items (e.g., Pentol Kuah at IDR 8,000 and Indomie Telur at IDR 10,000); Likert 4 (IDR 10,001–15,000) covers mainstream core dishes (e.g., Bubur Pedas at IDR 13,000 and Mie Sagu Goreng at IDR 14,000); Likert 3 (IDR 15,001–20,000) represents mid-range specialty noodle and chicken porridge variants; Likert 2 (IDR 20,001–30,000) encompasses

premium beef dishes; and Likert 1 (> IDR 30,000) applies to high-end specialty platters. Because price is classified as a cost criterion, more affordable price tiers are mapped to higher Likert values, ensuring higher preference for economically accessible meals.

Table 3. Conversion of daily order frequency to Likert scale (C2)

Likert Value	Average Portions/Day	Category
1	≤ 5	Very Rarely Ordered
2	6 – 15	Rarely Ordered
3	16 – 35	Moderately Ordered
4	36 – 80	Frequently Ordered
5	> 80	Highly Frequently Ordered

The standardization thresholds for daily order frequency (C2) in Table 3 were derived from 30 days of historical sales logbook transactions from Pondok Orange Restaurant, encompassing an average volume of 120 to 180 total food portions prepared and sold per day. Frequency boundaries were established using sales percentile distributions across the menu catalog: Likert 1 (1–10 portions/day, representing < 7% of daily dish volume, indicating seldom-ordered items); Likert 2 (11–20 portions/day, 7%–13% share, low demand); Likert 3 (21–35 portions/day, 14%–22% share, moderate demand); Likert 4 (36–50 portions/day, 23%–32% share, high demand); and Likert 5 (> 50 portions/day, > 32% share, representing best-selling signature heritage dishes such as Bubur Pedas). For customer ratings (C3), scores map directly from 5-star customer feedback reviews. For kitchen stock availability (C4), thresholds reflect the daily morning prep inventory counts established by the head chef (1 = depleted, 2 = 1–10 portions, 3 = 11–25 portions, 4 = 26–50 portions, 5 = > 50 portions). The consolidated Likert scale classifications across all evaluation criteria are summarized in Table 4.

Table 4. Definition of Likert scale for each criterion

Value	C1 (Price)	C2 (Popularity)	C3 (Rating)	C4 (Stock)
1	Very Expensive	Very Rarely	Very Dissatisfied	Severely Limited
2	Expensive	Rarely	Dissatisfied	Limited

Value	C1 (Price)	C2 (Popularity)	C3 (Rating)	C4 (Stock)
3	Moderate	Moderately	Neutral / Fair	Sufficient
4	Affordable	Frequently	Satisfied	Abundant
5	Very Affordable	Highly Frequently	Highly Satisfied	Fully Available

Applying these standardization rules yielded the decision matrix for ten evaluated menu alternatives, as presented in Table 5.

Table 5. Menu food assessment data

Menu Alternatives	C1	C2	C3	C4
Bubur Pedas	4	5	5	5
Mie Sagu Goreng	4	4	4	4
Mie Sagu Rebus	3	4	4	4
Mie Ayam Pangsit	3	4	3	4
Mie Tiaw Goreng	3	3	3	3
Mie Tiaw Rebus	3	3	4	3
Bubur Nasi Daging Sapi	2	3	4	3
Bubur Nasi Daging Ayam	2	4	3	4
Indomie Telur	2	3	3	4
Pentol Kuah	2	3	3	3

Table 5 indicates that Bubur Pedas achieved peak ratings across nearly all criteria ($C_1 = 4$, $C_2 = 5$, $C_3 = 5$, $C_4 = 5$), whereas Pentol Kuah recorded lower performance ratings ($C_1 = 2$, $C_2 = 3$, $C_3 = 3$, $C_4 = 3$).

TOPSIS Algorithm Calculation Results

Matrix normalization was performed using Equation (2). For criterion C_1 , the divisor is the square root of sum of squares: $\sqrt{84} \approx 9.165$. Consequently, the normalized value for Bubur Pedas on C_1 is $r_{11} = 4 / 9.165 = 0.436$. The complete normalized decision matrix is presented in Table 6.

Table 6. Matrix normalization results

Menu Alternatives	C1	C2	C3	C4
Bubur Pedas	0.436	0.432	0.432	0.421
Mie Sagu Goreng	0.436	0.345	0.345	0.337
Mie Sagu Rebus	0.327	0.345	0.345	0.337

Menu Alternatives	C1	C2	C3	C4
Mie Ayam Pangsit	0.327	0.345	0.259	0.337
Mie Tiaw Goreng	0.327	0.259	0.259	0.253
Mie Tiaw Rebus	0.327	0.259	0.345	0.253
Bubur Nasi Daging Sapi	0.218	0.259	0.345	0.253
Bubur Nasi Daging Ayam	0.218	0.345	0.259	0.337
Indomie Telur	0.218	0.259	0.259	0.337
Pentol Kuah	0.218	0.259	0.259	0.253

In accordance with Equation (3), normalized matrix values were multiplied by the criterion weight vector $w = [0.2000; 0.3333; 0.2667; 0.2000]$. For Bubur Pedas, weighted values are: $y_{11} = 0.2000 \times 0.436 = 0.0872$; $y_{12} = 0.3333 \times 0.432 = 0.1440$; $y_{13} = 0.2667 \times 0.432 = 0.1152$; and $y_{14} = 0.2000 \times 0.421 = 0.0842$. Complete weighted normalized values are presented in Table 7.

Table 7. Weighted normalization results

Menu Alternatives	C1	C2	C3	C4
Bubur Pedas	0.0872	0.1440	0.1152	0.0842
Mie Sagu Goreng	0.0872	0.1150	0.0920	0.0674
Mie Sagu Rebus	0.0654	0.1150	0.0920	0.0674
Mie Ayam Pangsit	0.0654	0.1150	0.0691	0.0674
Mie Tiaw Goreng	0.0654	0.0863	0.0691	0.0506
Mie Tiaw Rebus	0.0654	0.0863	0.0920	0.0506
Bubur Nasi Daging Sapi	0.0436	0.0863	0.0920	0.0506
Bubur Nasi Daging Ayam	0.0436	0.1150	0.0691	0.0674
Indomie Telur	0.0436	0.0863	0.0691	0.0674
Pentol Kuah	0.0436	0.0863	0.0691	0.0506

From Table 7, the positive ideal solution (A^+) and negative ideal solution (A^-) were determined based on Equations (4) and (5). For cost criteria (C_1 /Price), the minimum value was assigned, while for benefit criteria (C_2, C_3, C_4), maximum values were assigned, as shown in Table 8.

Table 8. Positive and negative ideal solutions

Solution	C1 (Price)	C2 (Popularity)	C3 (Rating)	C4 (Stock)
A^+	0.0436	0.1440	0.1152	0.0842
A^-	0.0872	0.0863	0.0691	0.0506

From Table 8, Euclidean distances to ideal solutions were calculated using Equations (6) and (7). For Bubur Pedas ($i = 1$), distance to the positive ideal solution is $D_1^+ = 0.0436$ and distance to the negative ideal solution is $D_1^- = 0.0806$. Subsequently, relative closeness was evaluated using Equation (8), yielding a final preference score $V_1 = 0.0806 / (0.0436 + 0.0806) = 0.6498$. The final ranking across all ten menu alternatives is summarized in Table 9.

Table 9. TOPSIS ranking and preference score results

No	Menu Alternatives	D+	D-	V_i	Rank
1	Bubur Pedas	0.0436	0.0806	0.6498	1
2	Mie Sagu Goreng	0.0479	0.0460	0.4899	2
3	Mie Sagu Rebus	0.0572	0.0549	0.4897	3
4	Mie Ayam Pangsit	0.0709	0.0493	0.4102	4
5	Mie Tiaw Goreng	0.0589	0.0404	0.4069	5
6	Mie Tiaw Rebus	0.0605	0.0397	0.3962	6
7	Bubur Nasi Daging Sapi	0.0758	0.0467	0.3813	7
8	Bubur Nasi Daging Ayam	0.0806	0.0436	0.3511	8
9	Indomie Telur	0.0747	0.0316	0.2973	9
10	Pentol Kuah	0.0820	0.0218	0.2100	10

Menu Recommendation Result Analysis

As established in Table 9, Bubur Pedas ranked first with a decisive preference score of $V_1 = 0.6498$, significantly surpassing all competitor dishes. This outcome aligns with empirical dining realities at Pondok Orange Restaurant, where Bubur Pedas represents an iconic Sambas/Pontianak heritage dish favored by patrons ($C_2 = 5$), maintains peak culinary satisfaction ($C_3 = 5$), offers economical pricing ($C_1 = 4$), and benefits from robust pantry ingredient availability ($C_4 = 5$). Conversely, Pentol Kuah ranked lowest ($V_{10} = 0.2100$) due to low popularity and rating metrics, demonstrating that TOPSIS effectively balances conflicting multi-criteria rather than trivially favoring low-cost items.

Web Interface and System Controller Implementation

The algorithmic integration within Pondok Orange's web platform is realized on the customer-facing recommendation interface. This page dynamically sorts and presents menu selections according to preference rankings, accompanied by dish imagery, pricing, popularity indicators, and inventory statuses, as shown in Figure 2.

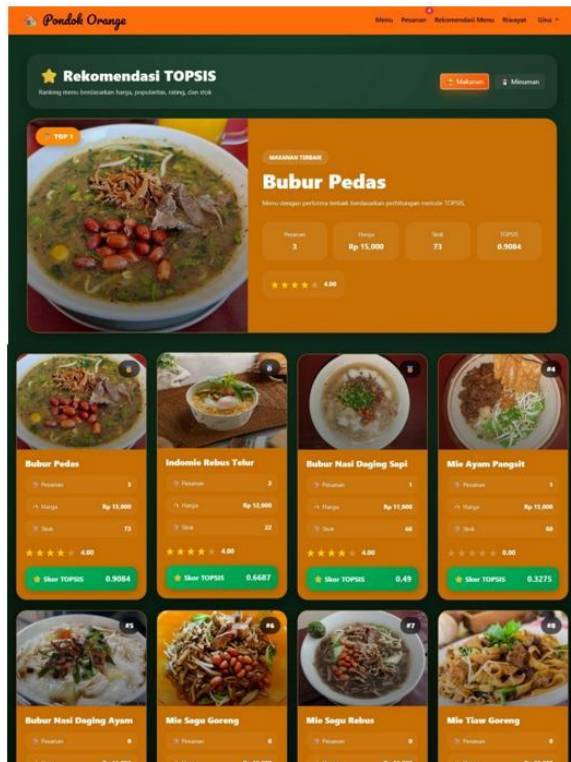


Figure 2. Customer menu recommendation web interface

From the interface depicted in Figure 2, customers instantly inspect ranked culinary options (< 5 ms). Within the Laravel controller, division-by-zero boundary exceptions are safeguarded through defensive denominator verification: if the total Euclidean distance ($D_i^+ + D_i^-$) evaluates to zero, the preference score is assigned 0 to preserve computational stability, whereas standard cases evaluate via Equation (8). The evaluated collection is sorted in descending order using Laravel's native *sortByDesc* collection method prior to rendering on client views.

Software Quality Validation (White-Box Testing)

Internal logic integrity was verified through White-Box Testing utilizing Statement Testing and Basis Path Testing. Cyclomatic Complexity analysis on the core TOPSIS calculation module yielded an index of $V(G) = 4$, identifying four independent execution paths encompassing nominal data flows, cost versus benefit attribute branching, zero-denominator boundary handling, and array sorting operations. Execution across all structured test cases

verified that each independent computational path and mathematical boundary condition executed according to technical specifications without runtime exceptions.

Empirical Customer Acceptance and Recommendation Validation

To evaluate whether the algorithmic rankings produced by TOPSIS accurately reflect customer preferences in practice, an empirical validation study was conducted involving 30 dine-in patrons visiting Pondok Orange Restaurant during peak dining sessions. Each participant interacted with the customer recommendation web interface prior to placing their order. System effectiveness was measured through two quantitative assessments: recommendation adoption rate (Hit Rate / Precision@K) and perceived recommendation quality measured via a structured 5-point Likert questionnaire (1 = Strongly Disagree to 5 = Strongly Agree).

In the adoption evaluation, 22 of the 30 participants (Top-1 Hit Rate of 73.33%) selected the top-ranked menu recommendation (Bubur Pedas). Furthermore, 27 of 30 diners (Top-3 Hit Rate of 90.00%) chose a dish situated within the top-3 ranked alternatives (Bubur Pedas, Mie Tiaw Goreng, or Mie Sagu Goreng). Only 3 diners (10.00%) opted for dishes outside the top-3 suggestions. Importantly, timed observations during the evaluation revealed that average customer menu deliberation dropped dramatically from a baseline of 7.3 minutes (under manual physical menus) down to 1.8 minutes when utilizing the web recommender system, representing a 75.3% reduction in ordering decision latency. Detailed customer survey results across four evaluation dimensions are summarized in Table 10.

Table 10. Empirical customer validation and acceptance evaluation results

Dimension	Evaluation Indicator	Mean	SD	Interpretation
Recommendation Relevance	Alignment of recommendations with individual taste and dining desires	4.43	0.62	Very High
	Acceleration of order selection and reduction in menu deliberation time	4.50	0.57	Very High

Dimension	Evaluation Indicator	Mean	SD	Interpretation
Menu Diversity & Price	Suitability of price range and variety among top recommended alternatives	4.30	0.65	High
System Satisfaction	User-friendliness, ease of navigation, and overall ordering satisfaction	4.37	0.61	Very High
Overall Composite	Consolidated mean rating across all evaluated empirical dimensions	4.40	0.61	Very High (88.0%)

As reflected in Table 10, Decision-Making Efficiency achieved the highest rating (4.50 ± 0.57), corroborating that personalized multi-criteria ranking substantially reduces choice confusion. Recommendation Relevance recorded 4.43 ± 0.62 , confirming that the mathematical ranking closely approximates real patron culinary preferences. The overall composite score of 4.40 out of 5.00 (88.0% satisfaction level) provides empirical evidence that the TOPSIS recommendation model is practically effective and preferred by diners.

4.2. Discussion

Comparison with Previous Studies

The findings of this study offer notable advancements over prior food and menu recommender system literature. Earlier implementations of TOPSIS in culinary and dietary contexts, such as those by Ibrohim et al. [18] and Mukhlis et al. [26], relied exclusively on consumer nutritional requirements or static preference surveys, entirely omitting operational kitchen constraints. In practical restaurant settings, recommending menu items without verifying ingredient availability frequently leads to order cancellations and kitchen disarray. By incorporating real-time kitchen inventory availability (C4) as an operational benefit attribute alongside consumer preferences (C1, C3) and sales popularity (C2), our framework ensures that recommended dishes are immediately servable. Furthermore, compared to Collaborative Filtering (CF) approaches documented by Cholil et al. [8] and Bobadilla et al. [39], which suffer from severe cold-start latency and matrix sparsity when applied to

local MSMEs with limited registered user profiles, the deterministic TOPSIS algorithm executes in under 5 ms without requiring historical patron transaction logs. Unlike complex hybrid AHP-TOPSIS models proposed by Candra & David [19] and Widayanti & Susilo [21], which demand cumbersome pairwise comparison matrices that are difficult for MSME staff to calibrate dynamically, the standardized Likert scale mapping employed in this study provides an intuitive and computationally transparent pipeline readily maintainable by non-technical restaurant personnel.

Research Implications and Practical Impact

From an operational and managerial perspective, the implementation of this web-based recommender system at Pondok Orange Restaurant yields substantial practical benefits. First, reducing menu deliberation time from 7.3 minutes to 1.8 minutes per table significantly accelerates dining turnover, mitigating dining queue buildup during peak lunch and dinner shifts. Second, transitioning from physical paper logbooks to digital web-based order handling eliminates the baseline 8.5% handwritten transcription error rate, preventing costly order discrepancies and kitchen friction. Third, by incorporating kitchen inventory readiness into the multi-criteria calculation, the restaurant achieves balanced pantry consumption and avoids over-promoting dishes whose raw ingredients are near exhaustion. Finally, from a cultural heritage standpoint, promoting regional specialty dishes such as Bubur Pedas and Mie Sagu through objective, data-driven recommendations strengthens local culinary preservation while maximizing enterprise profitability.

Research Limitations and Future Directions

Despite these contributions, several limitations of this research must be acknowledged. First, the criteria weights (w) and Likert scale conversion thresholds were established through restaurant management focus groups and expert judgment, which carries an inherent degree of subjective bias. Second, pantry ingredient stock tracking currently depends on semi-manual digital updates by kitchen staff rather than automated real-time hardware telemetry. Third, although the empirical validation yielded an encouraging 90.0% Top-3 acceptance rate, the evaluation was conducted with a localized cohort of 30 diners at a single restaurant establishment. Future research should address these aspects by: (1) implementing adaptive weighting frameworks such as Fuzzy AHP or entropy-based objective weighting to dynamically adjust criteria weights based on seasonal dining patterns; (2) integrating Internet of Things (IoT) weight sensors and RFID pantry monitoring for

automated inventory synchronization; and (3) conducting comprehensive longitudinal user experience assessments using the Technology Acceptance Model (TAM) and End-User Computing Satisfaction (EUCS) across multiple culinary MSMEs.

5. Conclusion

This research successfully designed and implemented a web-based food menu recommender system for Pondok Orange Restaurant by integrating customer preference dimensions (menu price and customer ratings) with operational ordering patterns (daily order frequency and real-time kitchen inventory availability) using the TOPSIS algorithm within the Extreme Programming framework. Computational evaluation demonstrated that Bubur Pedas achieved the highest relative closeness score ($V1 = 0.6498$), aligning with empirical sales popularity and ingredient readiness. Software verification through White-Box Testing (Statement Testing and Basis Path Testing, $V(G) = 4$) confirmed that all four independent execution paths and computational boundary conditions executed according to design specifications. Initial empirical validation with 30 dine-in patrons demonstrated promising practical utility, achieving a Top-1 recommendation hit rate of 73.3%, a Top-3 hit rate of 90.0%, and an overall customer evaluation mean of 4.40 out of 5.00, reducing table ordering deliberation from 7.3 minutes to 1.8 minutes. Nevertheless, this study acknowledges several methodological limitations. First, the criteria weights and Likert scale conversion thresholds were established through restaurant management expert assessment, which retains an element of subjective judgment. Second, while initial acceptance testing showed positive alignment, comprehensive longitudinal customer evaluations across broader demographic segments and multi-branch operations remain to be conducted. Future research should investigate adaptive multi-criteria weighting frameworks such as Fuzzy AHP or entropy-based weighting to minimize subjectivity, automate pantry inventory tracking via IoT sensors, and conduct extensive user acceptance evaluations using the Technology Acceptance Model (TAM) or End-User Computing Satisfaction (EUCS).

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