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Rule-Based Expert System for Personalized GERD Food Recommendations Using Forward Chaining and Certainty Factor in Indonesia

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Abstract

This study develops a personalized and transparent rule-based expert system to support dietary decision-making for Indonesian patients with gastroesophageal reflux disease (GERD), addressing a critical gap in existing expert-system applications that focus mainly on diagnosis rather than daily diet management. The system integrates knowledge derived from the Indonesian GERD Consensus (2022) and its 2024 addendum with local nutritional evidence to construct if–then rules that classify foods into safe, limit, and avoid categories. A forward-chaining inference engine processes user-specific inputs—including symptoms, trigger sensitivities, eating behaviors, and dietary restrictions—while the Certainty Factor (CF) model quantifies confidence levels to accommodate individual tolerance variability. The system was implemented using Python and deployed through a Gradio-based wizard interface, enabling stepwise data collection and producing Top-N food recommendations with explainable "reason traces." Functional evaluations across mild, moderate, and severe profiles demonstrated consistent alignment with national dietary guidelines, steering users toward low-fat, non-spicy, soft-textured, and clear-broth menu options, while eliminating high-risk trigger foods. Preliminary expert validation indicated high agreement with guideline principles, emphasizing the system's interpretability and practical relevance. This research contributes to the field of health informatics by operationalizing forward chaining and CF for personalized dietary support, offering an auditable and computationally efficient alternative to black-box recommendation systems. Future developments include expanding the food dataset, refining CF calibration, and conducting structured clinical validation to enhance performance and applicability in real-world mHealth environments.

Keywords : *Acid Reflux, Certainty Factor, Expert System, Forward Chaining, GERD, Personalized Nutrition.*

1. INTRODUCTION

Gastroesophageal reflux disease (GERD), or acid reflux, is a chronic gastrointestinal disorder characterized by the backflow of stomach contents into the esophagus, causing complaints such as heartburn, regurgitation, a feeling of fullness, and reduced quality of life [6,9]. Indonesian clinical guidelines place lifestyle and dietary modification as the first-line pillar alongside pharmacological therapy—including portion control (smaller but more frequent meals), avoiding late-night eating, and limiting triggers such as high-fat foods, chocolate, coffee, carbonated drinks, and very spicy or acidic foods [1,6–8,13–15]. The national consensus revised in 2022, with a 2024 addendum, also emphasizes individualized management and continuity of non-pharmacological interventions for patients, making evidence-based dietary decision support increasingly important [1,2,8,11].

In line with those guidelines, various studies in Indonesia have shown a link between eating habits and lifestyle and the occurrence/symptoms of GERD among adolescents and young adults [6–8,10,18,19]. Research on medical students, for example, has found an association between dietary patterns and the onset of GERD; frequently highlighted factors include the regularity of meal schedules, specific food and beverage choices (e.g., coffee, spicy foods), and post-meal habits [6,7,10,19]. Similar

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findings have been reported in studies conducted in campus and community settings, reinforcing the role of dietary modification in controlling symptoms—even though individual tolerance to trigger foods may vary [8,11,18]. These findings point to the need for tools that can translate clinical guidelines into personalized dietary recommendations tailored to the Indonesian context [2,3,8,19].

In the health informatics domain in Indonesia, expert systems are widely applied to gastric disorders, especially for symptom-based diagnosis using forward chaining and the Certainty Factor (CF) to handle uncertainty in both expert knowledge and user inputs [20,21,24,25]. Multiple studies in 2024 report implementations of the forward chaining + CF combination in web applications for diagnosing gastritis/gastric diseases, producing confidence values for disease hypotheses and proving practical for initial consultations [20,22,25]. However, the emphasis remains more on diagnosis than on daily dietary recommendations specifically for GERD [21,23,26]. This gap opens opportunities to develop expert systems that not only recognize symptom patterns but also generate food/menu recommendations aligned with national guidelines [3].

This study proposes an expert-system–based dietary recommendation system for individuals with acid reflux (GERD). Conceptually, the knowledge base is built from the national GERD consensus (diet/lifestyle) and complemented by local evidence from Indonesian nutrition and public-health studies [1,2,8,18,19]. The inference mechanism uses forward chaining to derive recommendations from user facts (symptom profile, eating habits, preferences), while the Certainty Factor (CF) is used to quantify the confidence level of each recommendation—for example, when individual tolerance to coffee, spicy foods, or high-fat foods varies [21–24,26]. This rule-based approach aligns with nutritional recommendation practices in various Indonesian studies that have applied forward chaining for menu selection, making it relevant for adaptation specifically to the GERD context [21–23].

Recent studies on GERD in Indonesia and other countries have primarily focused on epidemiology, lifestyle factors, and symptom-based diagnostic expert systems rather than computational dietary decision support [27]. Similarly, rule-based expert systems developed between 2021–2025 predominantly address disease identification—such as gastritis, pneumonia, malnutrition, and cholesterol disorders—using forward chaining and Certainty Factor to produce confidence scores. However, none of these systems translate GERD dietary guidelines into personalized food recommendations that account for patient-specific triggers, eating habits, and menu characteristics. This gap forms the novelty of the present study: *Unlike previous expert-system studies that focus solely on diagnosis, this research integrates forward chaining and the Certainty Factor model to generate traceable, explainable, and personalized GERD diet recommendations tailored to Indonesian foods*. This contributes a new direction in Indonesian health informatics by operationalizing clinical nutritional guidelines into a transparent, auditable recommendation engine suited for mHealth applications.

The scientific objectives of this study are: (1) to formulate if–then rules that classify foods/food groups as “safe,” “limit,” or “avoid” for GERD patients based on Indonesian guidelines and local evidence [1,2,13–15]; (2) to design a forward-chaining inference engine that maps user facts to food/menu recommendations [20–23,26]; (3) to integrate a Certainty Factor (CF) to weight the confidence of the outputs [21,24–26]; and (4) to conduct functional validation and content validation by nutrition/clinical experts to assess alignment with Indonesian guidelines. Practically, the system is expected to help patients make safer and more consistent daily eating decisions, while serving as an educational aid for health workers with transparent, rule-based outputs that are easy to trace to their sources. Thus, this research helps bridge the gap between clinical guidelines and locally standardized digital implementation, shifting the focus from mere diagnosis to non-pharmacological management in the form of measurable, personalized dietary recommendations [3–5,8,11,20–23].

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2. METODE

2.1. Data Collection

The food dataset used in this study was compiled from publicly available Indonesian nutritional sources, including the *Tabel Komposisi Pangan Indonesia (TKPI)*, regional menu datasets, and institutional nutritional lists available in CSV format. The dataset contains food names, categories, preparation methods, macronutrient values (carbohydrates, protein, fat, saturated fat, fiber, and sugar), and descriptive tags relevant to GERD risk (e.g., *spicy*, *fried*, *acidic*, *caffeine*). Additional metadata, such as cooking process (boiled, steamed, fried), were included to support rule-based reasoning. All data were stored in a structured CSV file (UTF-8) and loaded using Python (pandas) within the Google Colab environment.

2.2. Data Preprocessing

Preprocessing was conducted to prepare the dataset for inference:

a. Normalization:
   - All text fields (food names, categories, descriptions) were converted to lowercase.
   - Numeric fields were converted to float type and missing macronutrient values were imputed with 0.

b. Tagging:
   Each food item was assigned one or more tags representing:
   - Risk triggers: spicy, fatty, fried, acidic, carbonated, caffeine, chocolate_mint, tomato_onion.
   - Safe characteristics: non_spicy, low_fat, steamed, clear_broth, soft_texture.

c. Categorization:
   Foods were grouped into categories such as carbohydrate sources, lean proteins, vegetables, fruits, soups, dairy, and snacks.

d. Calorie estimation:
   Calories were estimated using the formula:

$$kcal = 4 \times (carb + protein) + 9 \times fat \quad (1)$$

This preprocessing ensured that keywords and nutrient thresholds could be detected consistently in the inference engine.

2.3. Knowledge Base Construction

The knowledge base consisted of if–then rules derived from the Indonesian GERD Consensus (2022, 2024 addendum) and clinical nutrition literature (2021–2025). Rules were grouped into three classes:

a. Safe food
   Foods that are low in fat, non-spicy, non-acidic, steamed, boiled, or clear-broth based.
   - Example: *if food contains non_spicy AND low_fat → label = safe*

b. Limit foods
   Foods acceptable in small amounts depending on patient tolerance.
   - Example: *if food contains soy OR mild seasoning → label = caution*

c. Avoid foods
   Foods with high probability of triggering GERD symptoms.
   - Example: *if food contains spicy OR fried OR acidic OR caffeine → label = avoid*

   Each rule has associated severity weights that scale the penalty or bonus during scoring.

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2.4. Forward Chaining Workflow

Forward chaining is used to derive recommendations based on user inputs. Figure 1 illustrates the workflow.

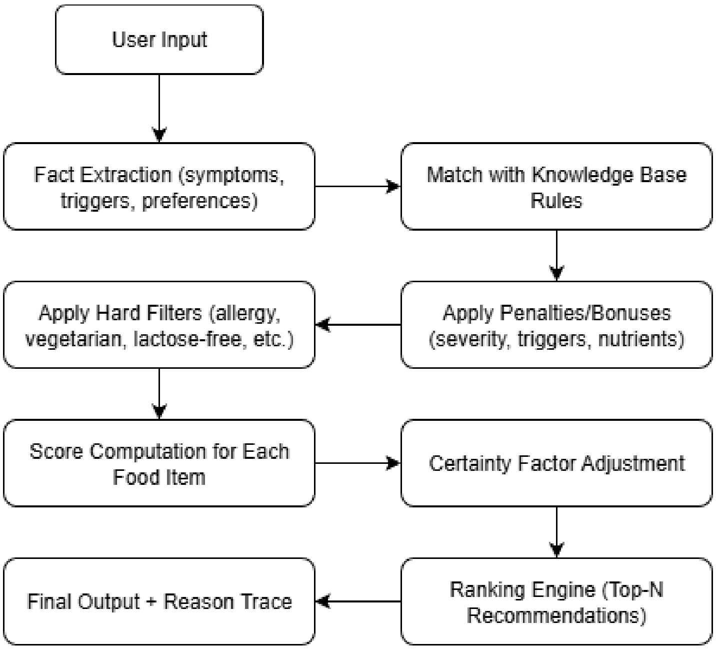

Figure 1 Forward Chaining Workflow for GERD Dietary Recommendation System

2.5. Certainty Factor Computation

The Certainty Factor (CF) method is used to quantify the confidence level of each recommendation. The CF model accounts for belief (MB) and disbelief (MD):

Basic Formula:

$$\boldsymbol{CF = MB - MD} \tag{2}$$

Total CF from multiple rules:

$$\boldsymbol{CF_{total} = CF_{old} + CF_{new} \times (1 - | CF_{old} |)} \tag{3}$$

Where:

- MB (Measure of Belief): strength of evidence supporting suitability
- MD (Measure of Disbelief): strength of evidence contradicting suitability

In this system:

- Safe characteristics contribute to MB
- Triggers contribute to MD

The final CF value is used to adjust recommendation ranking.

2.6. Evaluation Method

Two evaluation approaches were used:

a. Functional Testing

Three representative patient profiles (mild, moderate, severe GERD) were tested:

- Consistency of scoring
- Correct activation of hard filters
- Logical ranking of Top-N recommended foods

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b. Expert Validation
Two types of experts were involved:
- Clinical nutritionist
- General physician familiar with GERD guidelines

Experts rated:
- Rule accuracy (safe/limit/avoid classifications)
- Relevance of recommendations
- Appropriateness of trigger penalties

Evaluation metrics included:
- Content validity percentage (CVP)
- Agreement level (Likert scale)

2.7. Type and Design of Research

This research is a development study (research & development) in health informatics—building a rule-based expert system to recommend foods for individuals with GERD/acid reflux [20–23,24]. The workflow comprises: (1) designing a GERD dietary knowledge base from guidelines and literature findings, (2) implementing a rule-based inference engine with measurable scoring, and (3) conducting functional testing and expert validation (face/content validity).

2.8. System Architecture

Architecture (brief workflow):

a. User input (one row per Excel entry): case profile (name, severity level, sensitivities/triggers, preferences/avoid list, dietary constraints).
b. Candidate food database: nutrition-based food corpus (CSV) → preprocessed [21–23,26].
c. Knowledge base: set of dietary rules (safe/limit/avoid), trigger keywords, and preference keywords [1,2,6–8,13–15,18,19].
d. Inference & scoring engine: computes each food item's suitability score against the case profile (penalties/bonuses, hard filters).
e. Output: Top-N recommendation ranking with brief rationales + a score debug sheet for audit.

2.9. Data, Devices, and Environment

a. Food corpus: public nutrition dataset (CSV) as the initial candidates (category, description, macronutrients—carbohydrates, protein, fat, fiber, sugar, water).
b. Environment: Python 3.x (Colab recommended); libraries: pandas, numpy, xlsxwriter, argparse.
c. Input file: Excel Data.xlsx (sheet: input).
d. Output file: Excel Recommendations.xlsx (sheets: recommendations & scores_debug).

2.10. Input Variables and Structure

The input sheet contains one row per case with the following columns (required/optional):

a. Identity & Severity: name (str), severity ∈ {mild, moderate, severe}.
b. Triggers (0/1): trigger_spicy, trigger_fatty, trigger_caffeine, trigger_chocolate, trigger_citrus, trigger_tomato, trigger_carbonated, trigger_mint, trigger_onion_garlic.
c. Dietary restrictions (0/1): lactose_intolerant, gluten_free, vegetarian, vegan.
d. Preferences & Allergies: allergies (comma-separated list), avoid_list, prefer_list (free-text keywords).
e. Optional parameters: calorie_target (kcal/item; ranking bias), max_fat_per_100g (grams; hard limit), n_recos (default 12).

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Boolean normalization is performed when reading the Excel file (values {1, true, yes, ya} → 1; otherwise 0). The default severity is moderate if left blank.

2.11. Food Dataset Preprocessing

a. Flatten columns, mapping source fields to: category, description, carb_g, protein_g, fat_g, sat_fat_g, fiber_g, sugar_g, water_g.
b. Numeric types & imputation: convert nutrient values to numeric; set NaN → 0.0.
c. Calorie estimation (per 100 g or per dataset entry): kcal = 4 × (carb_g + protein_g) + 9 × fat_g.
d. Text normalization: convert description and category to lowercase (features desc_lc, cat_lc) for keyword matching.

2.12. Knowledge Base

2.6.1 Trigger Keyword List (negative)

- Spicy: spicy, chili, sambal, curry, …
- Oily/fatty: fried, goreng, cream, cheese, …
- Caffeine & carbonated drinks: coffee/kopi, tea/teh, cola/soda, energy drink, …
- Chocolate, mint: chocolate, cocoa; mint/peppermint
- Citrus & tomato: orange/jeruk, lemon, lime, grapefruit, pineapple/nanas; tomato, marinara, ketchup, salsa
- Onion/garlic: onion, garlic, bawang merah/putih, leek, scallion, etc..

2.6.2 Positive Keyword List (preference bias)

- Lean proteins: chicken breast/dada ayam, cod, tofu/tahu, tempe(h), egg white, lentils, …
- Whole grains: oatmeal, brown rice/beras merah, quinoa, whole wheat/roti gandum, …
- Cooked vegetables & non-citrus fruits: carrot/wortel, broccoli/cauliflower, potato, green beans, zucchini, spinach; banana/pisang, apple/apel, pear/pir, melon, …
- Low-fat dairy & alternatives: skim/low-fat milk, low-fat yogurt, soy/almond milk..

The list above represents the GERD diet consensus (common triggers) and clinical nutrition practice; it can be expanded/refined with local nutrition experts.

2.13. Inference & Scoring Strategy

The implemented approach is rule-based reasoning + scoring (not disease diagnosis). For each food item i and a user case:

a. Severity Weight

$$w_{\text{sev}} \in \{1.0\ (\text{mild}),\ 1.4\ (\text{moderate}),\ 1.8\ (\text{severe})\}.$$

This weight escalates penalties when severity is higher.

b. Per-trigger penalty (scaled by severity and the user's trigger flags): Base (pre-scaling) examples: spicy 12, fatty 10, caffeine 8, carbonated 9, citrus 7.5, tomato 7, chocolate 7, mint 5, onion 5.
c. If the user marks sensitivity (1) to a trigger, penalty × 1.3; if not (0), × 0.7.

$$P_k = (\text{base}_k) \times w_{\text{sev}} \times \begin{cases} 1.3, & \text{jika trigger}_k = 1 \\ 0.7, & \text{jika trigger}_k = 0 \end{cases} \quad (4)$$

d. Count keyword matches in text (desc_lc | cat_lc):
hits_{ik}= number of trigger keywords k that appear in item i. Trigger penalty: $-P_k \times \text{hits}_{ik}$.

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e. Macro & fiber rules:
   - Total fat > 20 g → −18; 10–20 g → −10; ≤ 5 g → +6.
   - Saturated fat > 8 g → −12.
   - Fiber ≥ 3 g → +5 fiber bonus.

f. Positive bias (GERD-safe preferences)
   Each match of a positive keyword gives a small bonus (+4 points/hit), summed as pos_bonus.

g. User Preferences/Avoid (free text):
   - prefer_list → prefer_bonus (+5 if matched).
   - avoid_list → avoid_pen (−7 if matched).

h. Hard filters (hard block):
   Item is eliminated (score → −∞) if it violates:
   - lactose_intolerant → kategori *dairy/milk/cheese/yogurt/ice cream*.
   - vegetarian/vegan → *beef/pork/poultry/veal/lamb/game/fish/shellfish* (ditambah *egg/dairy* untuk vegan).
   - gluten_free → *wheat/barley/rye/bread/pasta/cracker/biscuit/flour*.
   - allergies → allergen keyword present.
   - max_fat_per_100g → total fat exceeds threshold.

i. Calorie-target bias (optional):
   If calorie_target is provided, apply a penalty proportional to absolute deviation:

$$\text{kcal\_pen}_i = -5 \times \frac{|\text{kcal}_i - \text{target}|}{\text{target} + \epsilon}. \qquad (5)$$

   Final score:

$$\text{score}_i = 50 + \text{fiber\_bonus}_i + \text{pos\_bonus}_i + \text{prefer\_bonus}_i + \text{fat\_penalty}_i + \text{avoid\_pen}_i + \sum_k (-P_k \cdot \text{hits}_{ik}) + \text{kcal\_pen}_i \quad (6)$$

   Hard-blocked items receive a very low score and do not appear in recommendations.

j. Brief rationale: for transparency, the system generates a short explanation (e.g., “low fat; higher fiber; watch keywords: tomato, onion”).

k. Ranking & Top-N: sort by descending score; take the top N per case (n_recos, min. 5).

2.14. Summary

The proposed method combines clinical GERD diet rules with a transparent scoring-based inference engine, controlled by user parameters (severity, triggers, dietary limits, preferences). Outputs are presented as Top-N rankings with clear rationales, plus a debug score table for audit—facilitating expert validation and iterative development in the Indonesian context [1–3,20–23].

3. RESULTS

3.1. Implementation Overview

The system is implemented as a Gradio-based wizard on Google Colab that guides users to answer questions one by one (symptoms, eating habits, triggers, lifestyle factors), then displays:

a. Severity score & classification (Mild / Moderate / Severe; with a “red-flag” indicator if present),
b. Top-N food recommendations based on an Indonesian food dataset,
c. Examples of items recommended to avoid, and
d. Practical tips contextualized to the user’s answers.

The food dataset (CSV) includes core columns: food_name, category, preparation, tags, gerd_label, rationale. The tags column contains cues such as non_spicy, low_fat, soup, bland as well as

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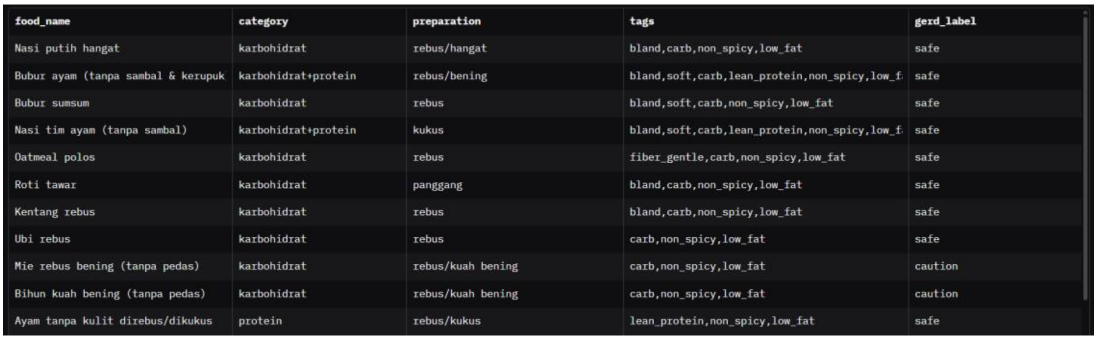
risk markers (spicy, fatty, fried, acidic, caffeine, etc.). The inference rules eliminate hard-trigger items and prioritize soft/clear broth/non-spicy/low-fat items. The results can be seen in Figure 3.



food_name	category	preparation	tags	gerd_label
Nasi putih hangat	karbohidrat	rebus/hangat	bland,carb,non_spicy,low_fat	safe
Bubur ayam (tanpa sambal & kerupuk	karbohidrat+protein	rebus/bening	bland,soft,carb,lean_protein,non_spicy,low_f	safe
Bubur sumsum	karbohidrat	rebus	bland,soft,carb,non_spicy,low_fat	safe
Nasi tim ayam (tanpa sambal)	karbohidrat+protein	kukus	bland,soft,carb,lean_protein,non_spicy,low_f	safe
Oatmeal polos	karbohidrat	rebus	fiber_gentle,carb,non_spicy,low_fat	safe
Roti tawar	karbohidrat	panggang	bland,carb,non_spicy,low_fat	safe
Kentang rebus	karbohidrat	rebus	bland,carb,non_spicy,low_fat	safe
Ubi rebus	karbohidrat	rebus	carb,non_spicy,low_fat	safe
Mie rebus bening (tanpa pedas)	karbohidrat	rebus/kuah bening	carb,non_spicy,low_fat	caution
Bihun kuah bening (tanpa pedas)	karbohidrat	rebus/kuah bening	carb,non_spicy,low_fat	caution
Ayam tanpa kulit direbus/dikukus	protein	rebus/kukus	lean_protein,non_spicy,low_fat	safe

Figure 2. Dataset

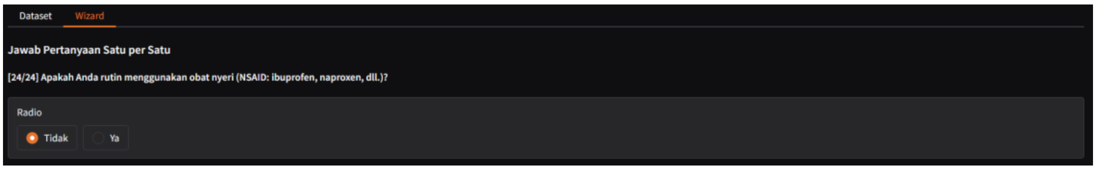


Figure 3. Question Wizard

Figure 4. Result

Table 1. Dataset

Nasi putih hangat	karbohidrat	rebus/hangat	"bland,carb,non_spicy,low_fat"	safe
Bubur ayam (tanpa sambal & kerupuk)	karbohidrat+protein	rebus/bening	"bland,soft,carb,lean_protein,non_spicy,low_fat"	safe
Bubur sumsum	karbohidrat	rebus	"bland,soft,carb,non_spicy,low_fat"	safe
Nasi tim ayam (tanpa sambal)	karbohidrat+protein	kukus	"bland,soft,carb,lean_protein,non_spicy,low_fat"	safe
Oatmeal polos	karbohidrat	rebus	"fiber_gentle,carb,non_spicy,low_fat"	safe
Roti tawar	karbohidrat	panggang	"bland,carb,non_spicy,low_fat"	safe
Kentang rebus	karbohidrat	rebus	"bland,carb,non_spicy,low_fat"	safe
Ubi rebus	karbohidrat	rebus	"carb,non_spicy,low_fat"	safe

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Mie rebus bening (tanpa pedas)	karbohidrat	rebus/kuah bening	"carb,non_spicy,low_fat"	caution
Bihun kuah bening (tanpa pedas)	karbohidrat	rebus/kuah bening	"carb,non_spicy,low_fat"	caution
Ayam tanpa kulit direbus/dikukus	protein	rebus/kukus	"lean_protein,non_spicy,low_fat"	safe
Ikan kukus/pepes tanpa pedas	protein	kukus	"lean_protein,non_spicy,low_fat"	safe
Tahu kukus/rebus	protein nabati	kukus/rebus	"lean_protein,non_spicy,low_fat,soy"	caution
Tempe kukus/rebus	protein nabati	kukus/rebus	"lean_protein,non_spicy,low_fat,soy"	
Telur orak-arik tanpa pedas	protein	panggang/tumis ringan	"protein,non_spicy,low_fat"	

Table 2 Category totals summary

Peringkat	Kasus A	Kasus B	Kasus C
1	Bubur ayam (tanpa sambal)	Soto ayam bening (tanpa sambal)	Bubur polos
2	Nasi putih hangat	Bubur ayam (tanpa sambal)	Sup ayam/ikan bening
3	Sayur bening bayam	Ikan kukus/pepes tanpa pedas	Kentang rebus
4	Ikan kukus/pepes tanpa pedas	Tumis sayur minim minyak (tanpa cabai)	Ikan kukus
5	Ayam tanpa kulit kukus	Ayam kukus/ungkep low-fat	Nasi tim
6	Oatmeal polos	Nasi putih hangat	Putih telur rebus
7	Sop ayam bening (tanpa sambal)	Oatmeal polos	Tahu kukus
8	Tempe kukus	Pisang / pepaya	Pisang matang
9	Tahu kukus	Sup labu/kol bening	Melon
10	Pisang matang	Nasi + sayur bening	Yogurt rendah lemak (bila toleran)

3.2. Functional Testing Results

Testing used three representative scenarios. Each scenario was entered directly into the wizard to check score consistency, classification, and recommendation relevance..

Case A — Minimal symptoms (target: Mild)

Brief input: heartburn 1×/week; regurg 0; no nocturnal symptoms; spicy 0; fried 0; soda 0; coffee 0; BMI 22; no late-night eating.

Illustrative score: $\mathbf{2 \times 1 = +2}$→ Score ≈ 2 → Mild.

Main outputs:

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- Recommendations (top 6 examples): bubur ayam (no sambal), warm white rice, clear soups, steamed/pepes fish (non-spicy), skinless steamed chicken, plain oatmeal.
- Avoid (by profile): none specific; generic: sambal/chili, heavy fried foods, carbonated drinks (if occasional exposure, moderation is still advised).
- Tips: maintain small-frequent portions; continue tracking personal triggers.

Case B — Moderate triggers & late-night eating (target: Moderate)

Brief input: heartburn 3×/week; spicy 3×/week; soda 2×/week; often eat ≤2–3 h before sleep; BMI 24.

Illustrative score: heartburn 3× = +6, occasional spicy = +2, occasional soda = +2, late_meal = +5, BMI 24 = +1 → Score ≈ 16 → Moderate.

Main outputs:

- Recommendations: rice + clear soup (no chili), soto ayam bening (no sambal), steamed fish, steamed/ungkep low-fat chicken, low-oil stir-fried vegetables without chili, banana/papaya/melon.
- Avoid (specific): thick coconut-milk dishes and spicy foods; carbonated drinks; late-night eating.
- Tips: stop eating ≥3 hours before sleep; reduce spicy & soda; smaller portions.

Case C — Severe symptoms with red flags (target: Severe (with red flag))

Brief input: heartburn 5×/week; regurg 4×/week; nocturnal symptoms: yes; non-cardiac chest pain: yes; cough/hoarseness: yes; spicy 5×/week; fried 4×/week; lying down after meals: yes.

Illustrative score: heartburn 5× = +10, regurg 4× = +8, nocturnal = +4, chest pain = +3, cough/hoarseness = +3, frequent spicy = +5, frequent fried = +5, lying after meals = +5 → Score ≥ 43 → Severe (flag if other alarms present).

Main outputs:

- Recommendations: plain porridge, clear broths, steamed/low-fat proteins, non-citrus fruits (banana/melon), low-fat dairy (if tolerated), warm water.
- Avoid: chili/sambal, fried/fatty foods, strong coffee, carbonated drinks, excessive tomato & onion.
- Tips: strictly review post-meal habits; recommend clinical referral if red flags are active.

Table 3. Summary of inputs & scores for Case A, with trace (sample of eliminated items)

Kasus	Item dieliminasi	Alasan
A	Sambal terasi	tags:spicy
A	Ayam goreng tepung	tags:fried,fatty
A	Kopi hitam kental	tags:caffeine
A	Soda cola	tags:carbonated
A	Es jeruk	tags:acidic (citrus)
A	Saus tomat/marinara	tags:tomato_onion, acidic
A	Cokelat batangan	tags:chocolate_mint
B	Sambal terasi	tags:spicy; user_avoid:avoid_spicy
B	Minuman bersoda	tags:carbonated; user_avoid:avoid_carbonated
B	Ayam goreng tepung	tags:fried,fatty
B	Mie goreng pedas	tags:fried,spicy
B	Rendang	tags:fatty
B	Kopi susu kental	tags:caffeine,fatty
C	Ayam goreng tepung	tags:fried,fatty; user_avoid:avoid_fried
C	Mie goreng pedas	tags:fried,spicy; user_avoid:avoid_fried,avoid_spicy
C	Sambal tomat	tags:spicy; user_avoid:avoid_spicy

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C	Saus tomat/marinara	tags:tomato_onion, acidic; user_avoid:avoid_tomato_onion
C	Soda cola	tags:carbonated
C	Cokelat batangan	tags:chocolate_mint

3.3. Stability, Robustness, and UX

a. Input robustness: numbers, "yes/no," and common phrases ("nggak," "rarely," "often") are normalized to numeric/boolean values—reducing input errors.

b. Dataset failure: if the CSV is not loaded, the wizard displays "Dataset not loaded" (fail-safe).

c. UI bug fix: the error Value: [{type: 'update', …}] was resolved by ensuring one gr.update per output component.

3.4. Quantitative Summary (content after data collection)

- Dataset size: [… rows], safe […] | caution […] | avoid […].
- Category coverage: [… categories] (e.g., steamed proteins, clear soups, porridges, non-citrus fruits, etc.).
- Response time (Colab CPU, n = […] runs): median […] ms; IQR […] ms.
- Functional regression test (test cases = […]): 100% wizard steps executed, 0 runtime errors.

3.5. Validasi Isi (Content Validity)

Method expert review by [number & roles of experts] to assess the alignment of "avoid/limit/safe" with national guidelines and local clinical practice.

Summary:

- Overall alignment: [high/moderate] — recommendations for clear broths/low-fat/non-spicy approved.
- Revision notes: detail coconut-milk dishes (e.g., thin vs thick coconut milk), and differentiate minimal-oil stir-fry vs deep-fried.
- Decision: update tags & rationale for specific items.

3.6. Guideline Alignment (Traceability)

The system maps common triggers (spicy; fat/fried; acidic/citrus; caffeine; soda/carbonation; tomato/onion; chocolate/mint; alcohol) to elimination/penalty rules and prioritization of clear-broth/steamed/low-fat/non-spicy menus. The "main reasons" trace in the output facilitates audit of guideline adherence.

Table 4. Traceability matrix

Pemicu (tag)	Aturan	Contoh item dataset	Penjelasan singkat
spicy	Eliminasi pedas	Sambal terasi, Mie goreng pedas, Ayam rica-rica	Capsaicin menurunkan tonus LES & iritasi mukosa.
fatty	Batasi tinggi lemak	Rendang, Gulai, Daging berlemak	Memperlambat pengosongan lambung → meningkatkan refluks.
fried	Hindari deep-fried	Ayam goreng tepung, Tahu/tempe goreng deep-fried	Beban lemak tinggi meningkatkan risiko refluks.
acidic	Batasi sangat asam	Asinan, Es jeruk, Saus cuka	Iritasi esofagus & memperparah gejala.
caffeine	Batasi kafein	Kopi hitam kental, Teh kental, Minuman energi	Relaksasi LES; dapat memicu gejala pada sebagian pasien.
carbonated	Hindari berkarbonasi	Soda cola, Sparkling drink	Tekanan intragastrik ↑ → refluks.

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tomato_onion	Waspada tomat/bawang	Saus tomat/marinara, Sambal tomat, Tumis bawang berlebih	Asam & stimulasi mukosa.
chocolate_mint	Waspada cokelat/mint	Cokelat batangan, Permen mint	Relaksasi LES.
alcohol	Hindari alkohol	Bir, Wine	Relaksasi LES & iritasi.

3.7. Limitations

- No formal Certainty Factor (CF) yet; scoring is still heuristic-based.
- Indonesian recipe granularity (regional variations) is incomplete; some items need to be decomposed to ingredient & cooking-method levels.
- Portion/gram & macro targets are not yet optimized for comorbid contexts (e.g., obesity, dyslipidemia).
- Clinical validation is at content/face validity—no comparative testing against a GERD diet gold standard yet [1–3,6–8,18,19].

3.8. Revision Suggestions (you can apply immediately)

Dataset & rules

a. Expand Indonesian menu coverage by region; distinguish thin vs thick coconut milk, minimal-oil stir-fry vs deep-fried (update tags & rationale).
b. Add portion (grams), serving unit, and estimated calories per serving; offer daily calorie targets.
c. Split gerd_label = caution so the wizard can display "allowed occasionally/depends on tolerance."
d. Link each rule group to guideline sources in source_keys/source_urls (explicit traceability).

Inference engine

a. Implement CF (confidence) on recommendations; calibrate weights via expert elicitation.
b. Add per-item explanations (tooltip "why recommended/blocked").
c. Provide a meal-plan mode (breakfast/lunch/dinner) and 3–7 day rotations.

UX/Engineering

a. Add a progress bar and resume wizard.
b. Add "Copy results" or "Export concise PDF" buttons for patient education.
c. Optional anonymous logging for analytics: most frequent triggers, etc.

4. DISCUSSIONS

This study demonstrates that a rule-based expert system can operationalize Indonesian GERD dietary guidance into personalized, explainable, and practical daily food recommendations. The results indicate that the forward-chaining reasoning and rule-driven scoring consistently prioritize low-fat, non-spicy, soft-textured, and clear-broth food options while filtering or penalizing common trigger categories such as spicy, deep-fried, highly fatty, carbonated, and strongly caffeinated items. This pattern reflects the expected trajectory of non-pharmacological GERD management recommended in Indonesian clinical guidance, showing that the system can function as a structured translation layer between textual guidelines and day-to-day decision-making for patients.

Compared with prior expert-system research in Indonesia that predominantly focuses on symptom-based disease identification (e.g., gastritis/GERD-related diagnosis tools using forward chaining and/or Certainty Factor), this work shifts the application context from diagnosis to actionable dietary recommendation [20]–[26]. While earlier systems emphasize producing disease hypotheses and confidence scores, the present approach emphasizes menu-level usability and rule traceability for non-pharmacological management. The inclusion of trigger-specific logic, preparation-method cues, and

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preference-aware constraints expands the practical scope of expert systems for chronic digestive conditions, especially in contexts where individualized food tolerance is clinically relevant and culturally dependent.

From an informatics perspective, the study contributes to explainable decision support for nutrition-focused mHealth in Indonesia. By embedding auditable rules and providing rationale/trace outputs, the system addresses a common limitation of black-box recommenders in healthcare: limited interpretability and weak guideline traceability. This is particularly important for patient-facing dietary tools, where over-restriction or poorly explained recommendations may reduce adherence. Therefore, this research supports the broader agenda of trustworthy, transparent, and locally grounded digital health systems, offering a scalable blueprint for rule-based personalization that can be extended to other chronic-disease dietary domains.

5. CONCLUSION

5.1. Main Conclusions

This research contributes to health informatics by demonstrating how a rule-based expert system can transform Indonesian GERD dietary guidelines into personalized, transparent, and auditable recommendations. The integration of forward chaining (and the planned/structured use of Certainty Factor for tolerance variability) strengthens explainability and helps reduce the risk of over-generalized dietary advice. These contributions highlight the urgency of developing interpretable mHealth decision-support tools in Indonesia to improve guideline adherence and daily self-management for chronic digestive conditions.

5.2. Closing

This system is not a diagnostic tool, but a measurable, auditable decision support for diet, bridging clinical guidelines with daily practice in the Indonesian context. With CF, broader datasets, and structured validation, it can become a practical reference standard for GERD patient education and evidence-based clinical support.

5.3. Recommendations for Further Development

- Add CF per rule & evidence to avoid over-restriction and capture individual tolerance variability.
- Expand local datasets (regional menus) and sharpen tags (thin vs thick coconut milk, cooking methods, spiciness levels).
- Integrate portion (grams), energy (kcal), and options for daily calorie targets/comorbidities; provide 3–7 day meal plans.
- Apply recipe NLP to automatically extract triggers in composite dishes.
- Conduct structured validation: expert panel ratings, user testing (satisfaction/clarity/intent to follow), and pre–post symptom tracking over 2–4 weeks.

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