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## Interactive Web-Based Expert System for Personalized Diet and Exercise Recommendations Using Forward Chaining

*Yunia Ikawati<sup>1\*</sup>, Bariq Abrar Ramadhan<sup>1</sup>*

<sup>1,\*</sup> Department of Informatics and Computer Engineering, Politeknik Elektronika Negeri Surabaya, Surabaya, Indonesia

\*Corresponding Author: [yunia@pens.ac.id](mailto:yunia@pens.ac.id)

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### Abstract

The rapid increase in lifestyle-related diseases such as obesity and hypertension highlight the urgent need for accessible and personalized digital health solutions. This study proposes and evaluates an interactive web-based expert system designed to deliver personalized diet and exercise recommendations using a forward chaining inference mechanism. The system analyzes individual user characteristics, including age, body mass index (BMI), health goals, dietary preferences, and physical activity levels, collected through a structured questionnaire. A knowledge base composed of expert-defined rules is employed to infer suitable diet plans (Mediterranean, low-fat, low-carbohydrate, and DASH diets) and exercise programs (cardio and strength training). The platform was developed using the Laravel framework and MySQL database, with a responsive user interface designed through Figma. System evaluation was conducted using black box testing and the System Usability Scale (SUS), which yielded a score of 78.38. The results demonstrate stable system functionality, fast response times, and high usability, indicating that the proposed system is effective in supporting personalized digital health recommendations. This research contributes to the field of health informatics by demonstrating the applicability of rule-based expert systems for personalized diet and exercise guidance.

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## 1. Introduction

Diet refers to the selection and regulation of food consumed by an individual or a population. It is commonly defined as a conscious effort to control and limit food intake with the goal of reducing or maintaining body weight. In essence, diet is a method of

managing eating patterns to achieve weight balance and overall health. Despite the abundance of information available on diet and fitness, many individuals struggle to find programs that suit their specific needs. This challenge often arises due to the lack of personalized recommendations provided by existing platforms.

According to the World Health Organization (WHO), obesity and overweight remain critical global health issues, with more than 2.5 billion adults classified as overweight and over 890 million suffering from obesity [1]. At the same time, public interest in physical exercise has significantly increased, reaching 78% in 2023 [2]. However, many people still face difficulties in adjusting their diet and exercise programs to accommodate changes in health conditions or personal preferences over time.

To address these challenges, recent studies have explored intelligent systems for personalized health recommendations. For instance, Garcia et al. developed a knowledge-based nutrition system called Virtual Dietitian using the Forward Chaining algorithm, which achieved a System Usability Scale (SUS) score of 83.4, indicating excellent usability [3]. Similarly, Naveed et al. proposed an IoT-based health monitoring system integrated with machine learning for personalized diet and exercise recommendations, demonstrating improved automation and efficiency in fitness management [4]. Other approaches, such as AI-driven recommender systems and chatbot-based frameworks, have also been introduced to enhance personalization and interactivity in nutrition guidance [5], [6].

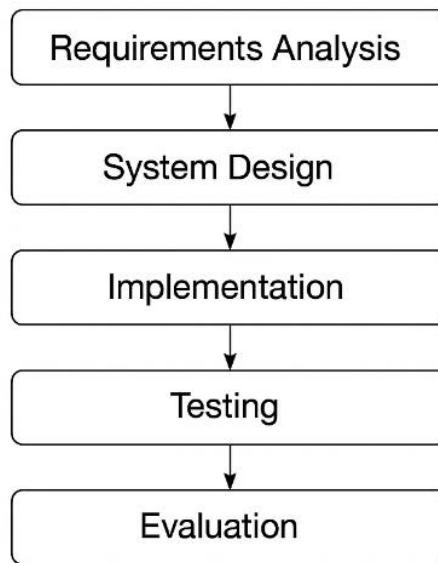
This research proposes an interactive web-based expert system that utilizes the Forward Chaining inference method to deliver personalized diet and exercise recommendations. Forward Chaining is a data-driven reasoning strategy that begins with known facts and applies rules whose premises match these facts to derive new conclusions until a goal is achieved or no further applicable rules remain [7]. It is widely used in expert systems due to its ability to process dynamic data and generate comprehensive inferences [8]. By leveraging this approach, the system can trace relevant rules to generate accurate and tailored recommendations.

The platform is accessible anytime and anywhere, enabling users to manage their diet and exercise programs conveniently. Through features such as questionnaires, progress tracking, and educational content, the system aims to enhance nutritional awareness, support digital health personalization, and contribute to obesity prevention efforts. This study contributes by designing and implementing a secure, responsive web-based expert system and evaluating its usability, performance, and security, thereby demonstrating the feasibility of rule-based personalization in digital health applications.

Different from existing approaches, this study uniquely integrates a rule-based Forward Chaining inference mechanism with an interactive web-based platform that simultaneously delivers personalized diet and exercise recommendations while supporting progress tracking, educational content, and usability evaluation. Unlike data-driven machine learning or black-box AI systems, the proposed method emphasizes transparent and explainable reasoning, allowing users to understand how recommendations are derived from their personal data. Furthermore, the system is systematically evaluated using the System Usability Scale (SUS), providing empirical evidence of its practical applicability. This combination of explainable rule-based reasoning, integrated health management features, and empirical usability validation represents the main methodological novelty of this research.

## 2. Methods

### 2.1 Research Design and Chronology



**Figure 1.** Research and Development Process

The research process consists of five main stages:

- Requirement Analysis: Identifying user needs and system specifications [9].
- System Design: Creating architecture diagrams, Entity Relationship Diagram (ERD), and Data Flow Diagrams [10].
- Implementation: Developing the platform using Laravel for backend, Blade for frontend, MySQL for database, and UI/UX design with Figma [11].
- Testing: Conducting functional, usability, performance, and security tests [12][13][14].
- Evaluation: Analyzing results based on usability scores, performance metrics, and security validation [14].

This study adopts a Research and Development (R&D) approach that follows a structured software development process, with Forward Chaining serving as the core reasoning mechanism of the expert system. The process begins with the requirements analysis phase, during which user data such as age, body mass index (BMI), health objectives, dietary preferences, and physical activity levels are identified. These data function as initial facts in the Forward Chaining inference process, making this stage essential for ensuring that the system can generate accurate and relevant recommendations. In the system design phase, expert knowledge related to nutrition and exercise is formalized into a set of IF-THEN production rules within a knowledge base. The Forward Chaining mechanism is designed as a data-driven reasoning process that starts from user-provided facts and iteratively matches them against rule premises to infer suitable diet and exercise recommendations.

The implementation phase translates the system design into a functional web-based expert system, in which the Forward Chaining inference engine systematically evaluates available facts and triggers applicable rules until a final conclusion is reached. This approach ensures that recommendations are produced logically and transparently based on the user's individual condition. During the testing phase, functional validation is performed using black box testing to confirm that the Forward Chaining process executes rules correctly and produces consistent outputs across different input scenarios. Finally,

the evaluation phase assesses the usability and effectiveness of the developed system using the System Usability Scale (SUS).

The uniqueness of the proposed method lies in the structured transformation of multi-dimensional user data into inference-ready facts, which are processed through a Forward Chaining mechanism to simultaneously infer dietary and exercise recommendations within a unified rule base. This approach enables modular rule expansion, consistency in decision-making, and explainability, distinguishing it from probabilistic or data-driven recommendation systems.

## 2.2 Research Procedure

The inference process applies Forward Chaining, which starts from known facts (user data) and iteratively applies rules whose premises match these facts to derive new conclusions until no further rules apply.

```

Require: User facts (age, weight, height, activity level, goals, health conditions)
Ensure: Personalized diet and exercise recommendations

1. Initialize WorkingMemory with user facts
2. Repeat
   For each rule in RuleBase:
      If rule.premises ⊆ WorkingMemory:
         Add rule.conclusion to WorkingMemory
         Output recommendation (diet/exercise/safety note)
3. Until no new facts can be inferred

```

**Figure 2.** Algorithm Forward Chaining Inference

## 2.3 Data Acquisition

User data were collected through a structured questionnaire, including:

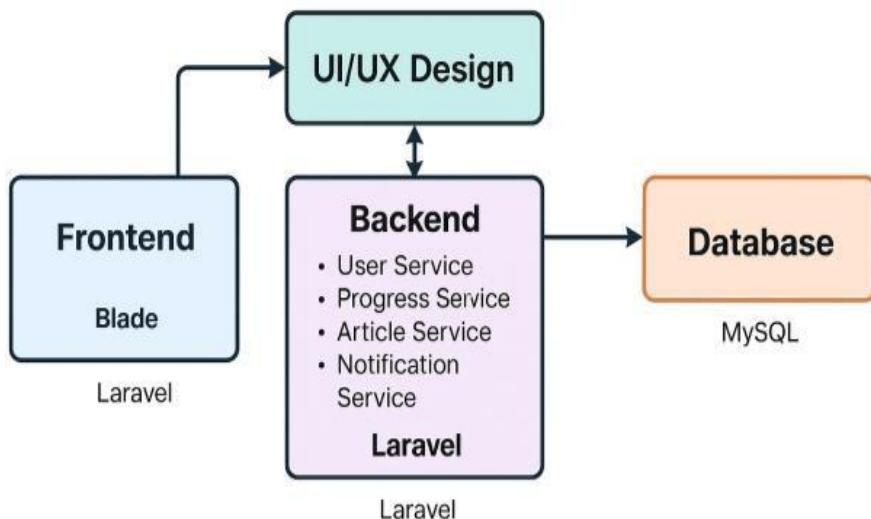
- Primary facts: age, gender, height, weight, activity level (sedentary, moderately active, extra active), health goals (weight loss, muscle gain, maintain weight), and medical conditions (hypertension, heart disease, dyslipidemia).
- Derived facts: Body Mass Index (BMI) calculated using:

$$\text{BMI} = \frac{\text{Weight (kg)}}{(\text{Height})^2 (\text{m})} \quad (1)$$

BMI categories: Underweight (<18.5), Normal (18.5–24.9), Overweight (25–29.9), Obese (>30).

## 2.4 System Architecture

The system architecture for this research in Figure 3 illustrates how the platform components interact to deliver personalized diet and exercise recommendations. It consists of three main layers: Frontend, Backend, and Database, supported by a UI/UX design layer.



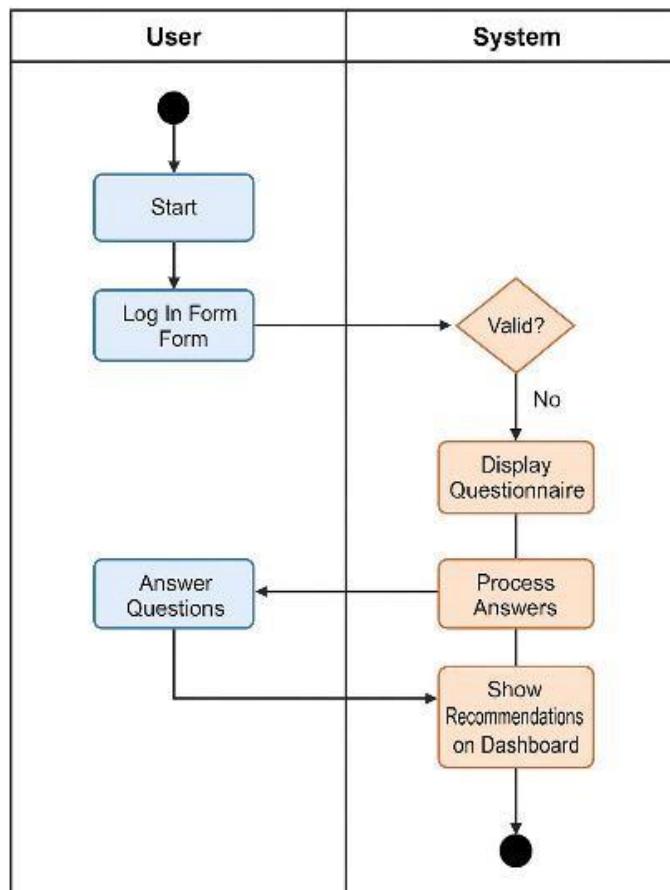
**Figure 3.** System Architecture

The Frontend, built using Laravel Blade, provides the user interface where users can log in, complete questionnaires, view recommendations, and track progress. The Backend, implemented with Laravel, handles core application logic and services such as user management, progress tracking, article management, and notifications. It also integrates the Forward Chaining inference engine, which processes user data and applies rule-based reasoning to generate personalized recommendations. The Database, powered by MySQL, stores user profiles, progress records, articles, and rule sets securely. The UI/UX design ensures a responsive and intuitive experience, connecting the frontend and backend seamlessly.

This architecture supports scalability, security, and real-time personalization, making it suitable for digital health applications focused on diet and exercise management.

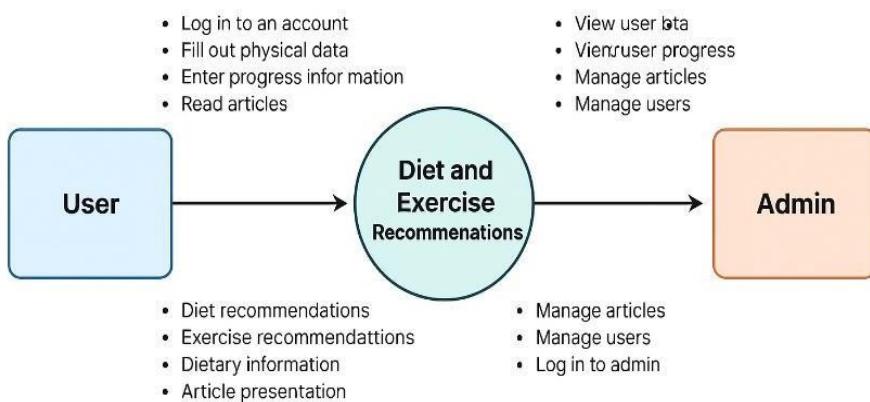
## 2.5 Activity Diagram

The activity diagram above illustrates the interaction between the User and the System during the recommendation process. The flow begins when the user starts and accesses the login form, then enters email and password. The system validates the credentials; if invalid, the user is prompted to retry. If valid, the system displays the questionnaire page, allowing the user to answer health-related questions. After submission, the system processes the answers using the Forward Chaining inference method and finally displays personalized diet and exercise recommendations on the dashboard. This diagram represents a clear sequence of actions for delivering tailored health guidance.



**Figure 4.** Activity Diagram for Diet and Exercise Recommendation System

## 2.6 Data Flow Diagram

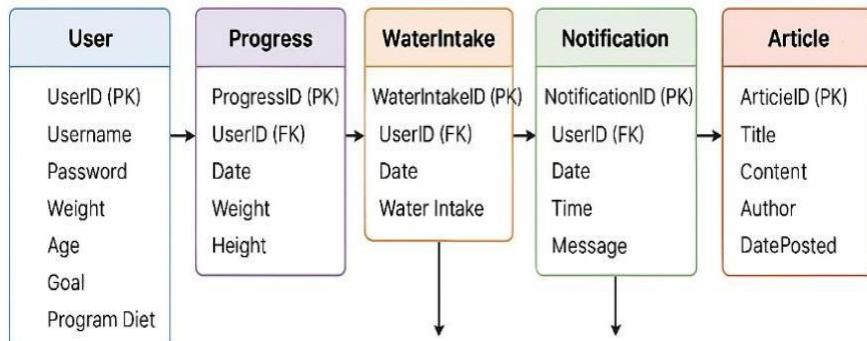


**Figure 5.** Data Flow Diagram for Diet and Exercise Recommendation System

The Data Flow Diagram (DFD) above illustrates the interaction between User, Admin, and the central process of generating diet and exercise recommendations. Users can log in, fill out physical data, enter progress information, and read articles, while receiving personalized outputs such as diet recommendations, exercise plans, dietary information, and article presentation. Administrators, on the other hand, manage articles, oversee user accounts, and monitor user progress through the system. The central process acts as the core logic, connecting both roles to ensure accurate recommendations.

and efficient content management. This structure supports personalized health guidance and streamlined administration in a web-based expert system.

## 2.7 Entity Relationship Diagram



**Figure 6.** Entity Relationship Diagram for Diet and Exercise Recommendation System

The ERD above represents the data structure of the web-based expert system for personalized diet and exercise recommendations. It consists of five main entities: User, which stores personal information such as username, password, weight, height, age, goal, and diet program; Progress, which records user progress data including date, weight, and height; WaterIntake, which tracks daily water consumption; Notification, which manages messages and reminders for users; and Article, which contains educational content with attributes like title, content, author, and date posted. Relationships are established through foreign keys linking these entities to the User table, ensuring data integrity and enabling personalized recommendations based on user profiles and progress.

## 3. Results and Discussion

### 3.1 Homepage Design of the Diet and Exercise Platform



**Figure 7.** Homepage of the Application

The result of the research shows that the developed application successfully provides an intuitive and visually appealing interface for users. The initial display of the diet and exercise platform features a clean, modern design with clear navigation options

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such as Start Program and Register for Free, emphasizing personalization and scientific methods. Key benefits, including personalized programs, evidence-based approaches, and measurable results, are highlighted on the homepage, ensuring users understand the value of the system. This user-friendly design supports the research objective of creating an accessible and engaging platform for personalized health recommendations.

### 3.2 Questionnaire Page

The series of questionnaires is designed to collect essential user information step by step for accurate personalization. The first page focuses on identifying the user's primary health goal, while the second gathers fundamental personal data such as gender, age, height, and weight, which are critical for BMI calculation and calorie estimation. The third page captures the user's daily activity level, an important factor in determining energy expenditure and exercise intensity. Subsequent steps include setting a realistic target weight and providing medical history, such as heart disease and hypertension, to ensure safe and tailored recommendations. Together, these questionnaires enable the system to generate precise diet and exercise plans using the Forward Chaining inference method.

(a)

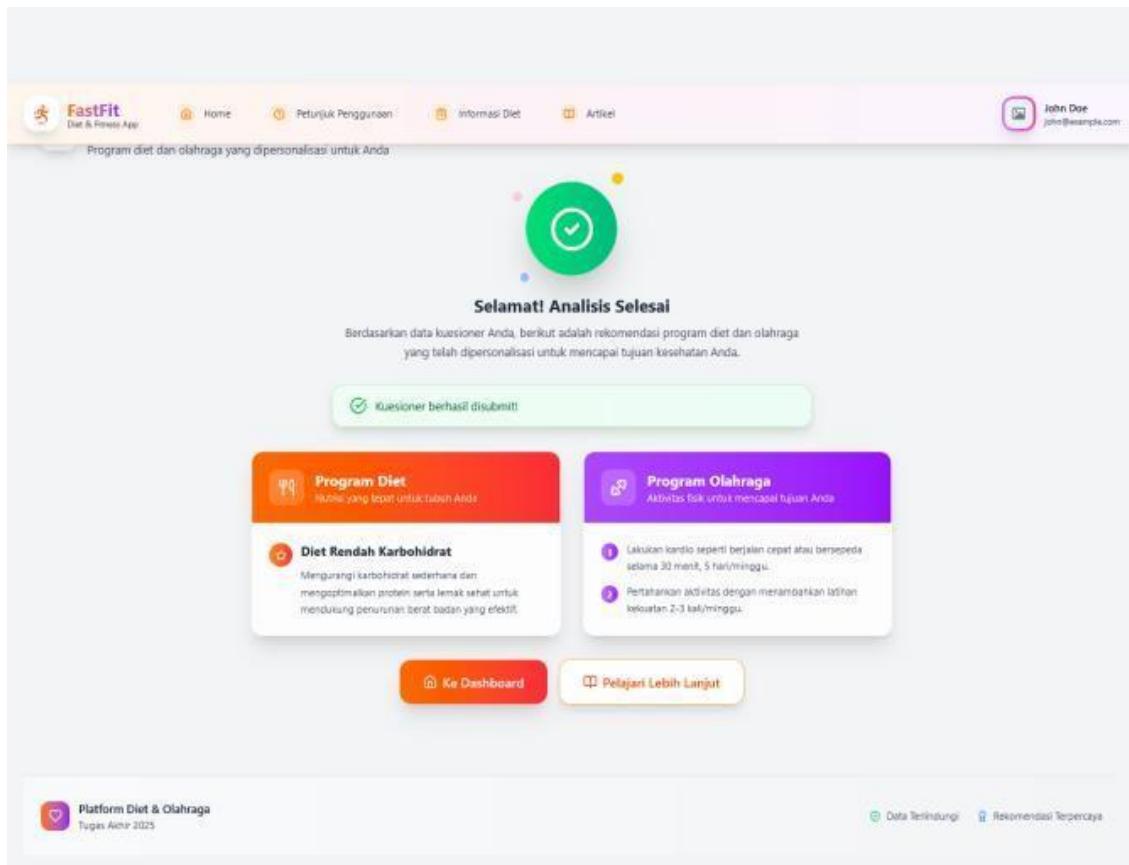
(b)

(c)

(d)

**Figure 8.** Questionnaire Interface (a), (b), (c) and (d)

### 3.3 Personalized Diet and Exercise Recommendations



**Figure 9.** Personalized Diet and Exercise Recommendation Page

The recommendation page shown above represents the final output after the system completes analyzing user data through the questionnaire. It clearly displays two separate cards: one for the Diet Program and another for the Exercise Program. In this example, the user is advised to follow a Low-Carbohydrate Diet and perform cardio exercises combined with strength training. Each recommendation includes a brief description and practical points to guide the user. Additionally, two action buttons are provided—one to navigate directly to the dashboard and another to explore detailed information about the recommendations. This design ensures clarity, usability, and supports the research goal of delivering personalized health guidance through a web-based expert system using the Forward Chaining method.

Garcia et al. developed Virtual Dietitian, a knowledge-based nutrition advisory system that also employed the Forward Chaining inference method and achieved a high usability score with a SUS value of 83.4 [3]. While both systems utilize rule-based reasoning to generate dietary recommendations, the system proposed in this study extends the scope by integrating both diet and exercise recommendations within a single interactive web-based platform. In addition, this research incorporates progress tracking and educational content, allowing users to continuously monitor and adjust their health programs, which was not emphasized in Garcia et al.'s implementation. Although the SUS score obtained in this study (78.38) is slightly lower, it still falls within the "GOOD" usability category, indicating strong user acceptance across diverse age groups.

In comparison with the work of Naveed et al., who introduced an IoT-based health monitoring system integrated with machine learning techniques [4], the proposed system adopts a rule-based Forward Chaining approach rather than data-driven machine learning models.

While IoT and machine learning offer higher automation and adaptability, they often operate as black-box systems with limited explainability. In contrast, the Forward Chaining mechanism employed in this study provides transparent and explainable reasoning, which is particularly important in health-related applications where user trust and interpretability are critical. This transparency allows users to better understand how recommendations are derived from their input data.

Other recent studies utilizing AI-based recommender systems and chatbot frameworks focus primarily on improving personalization and user engagement through conversational interfaces [5], [6]. However, these systems commonly rely on probabilistic or learning-based models that may require large datasets and continuous retraining. The system proposed in this research demonstrates that a rule-based expert system can still effectively deliver personalized recommendations with relatively low computational complexity, while maintaining consistency and reliability in decision-making.

Overall, the comparative analysis indicates that the proposed web-based expert system successfully balances personalization, explainability, and usability. By combining Forward Chaining inference with a structured software development approach and comprehensive usability evaluation, this study contributes a practical and scalable alternative to existing intelligent health recommendation systems. The findings reinforce the relevance of rule-based expert systems in digital health applications, particularly in contexts where transparency, ease of use, and rapid deployment are essential.

### 3.4 System Usability Scale (SUS) Testing Results for Web-Based Interactive Platform

Table 1 presents the individual System Usability Scale (SUS) scores obtained from 20 respondents across different age groups. The purpose of this table is to provide a clear overview of how each participant's usability perception contributes to the overall evaluation of the system. Each score was calculated using the standard SUS formula, where responses to the 10-item questionnaire were converted into adjusted values.

Result from the Table

- Total SUS Score = 1567.5
- Number of Respondents = 20
- Average SUS Score:

$$\frac{\text{Total SUS Score}}{\text{Number of Respondents}} = \frac{1567.5}{20} = 78.38 \quad (2)$$

The System Usability Scale (SUS) evaluation involved 20 respondents from diverse age groups (15–20, 21–30, and 41–50 years) to ensure a comprehensive usability assessment [12]. The average SUS score obtained was 78.38, which falls under the “GOOD” category according to standard interpretation. This indicates that the platform is not only acceptable but also considered easy and effective to use by most users across different age groups. Lower individual scores in certain age categories provide valuable insights for future improvements, such as simplifying workflows or adding guidance for users less familiar with technology.

**Tabel 1.** Summary of System Usability Scale (SUS) Scores

No	Responden	Age	Skor SUS
1	Responden 1	21-30	100.0
2	Responden 2	21-30	87.5
3	Responden 3	21-30	72.5
4	Responden 4	21-30	97.5
5	Responden 5	21-30	65.0
6	Responden 6	21-30	82.5
7	Responden 7	21-30	82.5
8	Responden 8	21-30	75.0
9	Responden 9	21-30	72.5
10	Responden 10	21-30	95.0
11	Responden 11	21-30	100.0
12	Responden 12	21-30	100.0
13	Responden 13	15-20	50.0
14	Responden 14	21-30	52.5
15	Responden 15	15-20	70.0
16	Responden 16	21-30	57.5
17	Responden 17	15-20	75.0
18	Responden 18	41-50	92.5
19	Responden 19	15-20	80.0
20	Responden 20	41-50	80.0
<b>Total Skor</b>		<b>1567.5</b>	

### 3.5. Forward Chaining Rule Design and Inferential Analysis

While previous subsections focus on system interfaces and usability outcomes, this section provides a critical analysis of the Forward Chaining inference mechanism that underpins the recommendation process. The expert system relies on a rule-based knowledge base, where domain knowledge related to nutrition and exercise is formalized into IF-THEN production rules. These rules were designed based on established dietary and physical activity guidelines derived from nutrition literature and validated health practices.

The rule design process begins by categorizing user input data—such as age, body mass index (BMI), health goals, activity level, and medical history—into structured facts. For example, BMI values are classified into categories such as underweight, normal, overweight, and obese, each serving as a triggering condition in the inference process. Health goals (e.g., weight loss or weight maintenance) and activity levels further refine the fact set, enabling the system to activate relevant rules in a data-driven manner.

The Forward Chaining mechanism systematically evaluates these facts against the rule base to generate intermediate conclusions before arriving at final recommendations. As an illustration, users with an overweight or obese BMI category, a weight loss objective, and moderate to high daily activity levels activate a set of rules that prioritize Low-Carbohydrate Diet recommendations. This is because such dietary patterns are associated with reduced caloric intake and improved short-term weight control, aligning with the system's expert-defined goals. In contrast, users with a normal BMI and balanced health objectives are more likely to trigger rules associated with the Mediterranean Diet, which emphasizes long-term cardiovascular health and nutritional balance rather than aggressive weight reduction.

Rule validation was conducted through consistency checking and expert review to ensure that no conflicting rules could be simultaneously triggered for the same user condition. Each recommendation pathway was tested using multiple simulated user profiles to confirm that the inferred outputs aligned with established dietary principles and safety considerations, particularly for users reporting medical conditions such as hypertension or heart disease. This validation process ensures that recommendations are not arbitrary but result from a transparent and logical inference process.

By explicitly linking user input conditions to rule activation and recommendation outcomes, the Forward Chaining approach provides a high level of explainability compared to black-box machine learning models. This interpretability allows both users and researchers to understand why specific diet and exercise programs are recommended, thereby increasing trust and reliability in health-related decision support systems. Consequently, the system demonstrates that rule-based reasoning, when carefully designed and validated, can effectively support personalized diet and exercise recommendations with both technical rigor and practical relevance.

#### 4. Conclusion

This study successfully developed an interactive web-based expert system that applies the Forward Chaining inference method to provide personalized diet and exercise recommendations. The system achieved its primary objective of delivering tailored guidance based on user-specific data, demonstrating strong usability with an average System Usability Scale (SUS) score of 78.38, categorized as "GOOD." These findings indicate that the platform is intuitive and effective for diverse user groups, supporting its potential as a practical tool for promoting healthy lifestyle management.

The research contributes to the advancement of digital health solutions by integrating rule-based reasoning for personalization, offering theoretical and practical implications for expert system design in healthcare. While the system performed well overall, minor usability variations among certain age groups suggest opportunities for improvement, such as simplifying navigation and enhancing user guidance. Future work should focus on expanding the knowledge base, integrating real-time data from wearable devices, and developing mobile applications to improve accessibility and personalization.

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#### 6. Author's Note

The authors declare that there is no conflict of interest regarding the publication of this article. Furthermore, the authors confirm that this manuscript is original, has not been published elsewhere, and is free from any form of plagiarism. All authors have contributed significantly to the research and preparation of this manuscript and agree with its submission for publication.

## 7. References

- [1] World Health Organization, "Obesity and overweight," Mar. 1, 2024. Accessed: Dec. 8, 2025. [Online]. Available: <https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight>
- [2] D. Hu, S. Zhou, Z. J. Crowley-McHattan, and Z. Liu, "Factors that influence participation in physical activity in school-aged children and adolescents: A systematic review from the social ecological model perspective," *Int. J. Environ. Res. Public Health*, vol. 18, no. 6, Art. no. 3147, 2021, doi: [10.3390/ijerph18063147](https://doi.org/10.3390/ijerph18063147).
- [3] M. B. Garcia, J. B. Mangaba, and C. C. Tanchoco, "Virtual Dietitian: A Nutrition Knowledge-Based System Using Forward Chaining Algorithm," in Proc. 2021 Int. Conf. Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT), Zallaq, Bahrain, Sep. 29–30, 2021. doi: [10.1109/3ICT53449.2021.9581887](https://doi.org/10.1109/3ICT53449.2021.9581887).
- [4] M. H. Naveed *et al.*, "IoT based health monitoring with diet, exercise and calories recommendation using machine learning," *Human-Centric Intelligent Systems*, vol. 5, pp. 246–258, Apr. 2025.
- [5] Z. Yang, E. Khatibi, N. Nagesh, M. Abbasian, I. Azimi, R. Jain, and A. M. Rahmani, "ChatDiet: Empowering personalized nutrition-oriented food recommender chatbots through an LLM-augmented framework," *Smart Health*, vol. 32, p. 100465, Jun. 2024, doi: [10.1016/j.smhl.2024.100465](https://doi.org/10.1016/j.smhl.2024.100465).
- [6] K. Lakshmi and C. M. Reddy, "Personalized fitness guidance using AI-driven recommendation systems," *J. Emerging Technol. Innov. Res.*, vol. 15, no. 6, pp. 56–63, 2024.
- [7] F. Hayes-Roth, D. A. Waterman, and D. B. Lenat, *Building Expert Systems*. Reading, MA, USA: Addison-Wesley, 1983.
- [8] Dijkstra, E. W., "On the Role of Scientific Thought," in *Selected Writings on Computing: A Personal Perspective, Texts and Monographs in Computer Science*. New York, NY, USA: Springer, 1982, doi: [10.1007/978-1-4612-5695-3 12](https://doi.org/10.1007/978-1-4612-5695-3_12).
- [9] I. Sommerville, *Software Engineering*, 10th ed. Boston, MA, USA: Pearson, 2016.
- [10] K. Rosenblatt, *Systems Analysis and Design*, 11th ed. Boston, MA, USA: Cengage Learning, 2018.
- [11] T. Otwell, "Laravel documentation." Accessed: Dec. 8, 2025. [Online]. Available: <https://laravel.com/docs>
- [12] J. Brooke, "SUS: A quick and dirty usability scale," in *Usability Evaluation in Industry*, P. W. Jordan, B. Thomas, B. A. Weerdmeester, and I. L. McClelland, Eds. London, U.K.: Taylor & Francis, 1996, pp. 189–194.
- [13] OWASP Foundation, "OWASP testing guide." Accessed: Dec. 8, 2025. [Online]. Available: <https://owasp.org>
- [14] Z. Sharfina and H. B. Santoso, "An Indonesian adaptation of the System Usability Scale (SUS)," in *Proc. Int. Conf. Adv. Comput. Sci. Inf. Syst. (ICACSIS)*, 2017, pp. 145–148.

## Authors Biographies



**Yunia Ikawati** is a lecturer at the Department of Informatics Engineering, Politeknik Elektronika Negeri Surabaya (PENS), Indonesia. Her academic and research interests include Mobile Application Development, Web Development, Machine Learning, Data Analysis, and Internet of Things (IoT).

Email: [yunia@pens.ac.id](mailto:yunia@pens.ac.id)

ORCID: [0000-0002-5093-8174](https://orcid.org/0000-0002-5093-8174)



**Bariq Abrar Ramadhan** is an undergraduate student in the Department of Informatics Engineering at Politeknik Elektronika Negeri Surabaya (PENS), Indonesia. His academic interests include web development, mobile applications, and intelligent systems.

Email: [bariqabramadhan@it.student.pens.ac.id](mailto:bariqabramadhan@it.student.pens.ac.id)

ORCID: -