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Mobile expert system for arm muscle training using forward chaining and best-first search

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ABSTRACT

Purpose: to develop a mobile-based expert system to provide personalized arm muscle exercise recommendations, addressing the limited availability of professional fitness instructors.
Method: this study used the waterfall development model, including analysis, design, implementation, and testing, and utilized J2ME and MySQL. Expert knowledge was obtained through interviews and literature review then formalized into if–then rules. The system applies forward chaining with best-first search optimization and was evaluated using black box testing and expert validation.
Findings: the mobile-based expert system successfully generates personalized arm muscle training recommendations based on user anthropometric data, providing accurate recommendations for exercise type, sets, repetitions, and load.
Implications: mobile-based expert systems can provide accessible, personalized, and reliable resistance training guidance, bridging the gap between beginner users and professional fitness expertise while demonstrating the potential of AI-based health technology in resource-limited environments.
Originality: combining forward chaining and best-first search in a mobile expert system to provide personalized arm training recommendations.

Introduction

Physical fitness plays a fundamental role in maintaining overall health, functional capacity, and quality of life. Resistance training, particularly weightlifting, has been widely recognized as an effective way to improve muscle strength, endurance, and body composition (Campo et al., 2021). Among the various muscle groups trained in resistance programs, the arm muscles comprising the biceps, triceps, and forearms are frequently emphasized due to their importance in upper-body performance and daily functional activities. Designing an effective resistance training program requires careful consideration of multiple variables, including exercise type, equipment selection, training intensity, number of sets, repetitions, and load progression (Jara et al., 2023). These parameters must be adjusted based on individual characteristics, such as height, weight, and overall physical condition, to ensure both safety and effectiveness. Inadequate program design may lead to suboptimal results or increase the risk of injury, particularly among beginners (Bonilla et al., 2022).

In practice, novice gym members often struggle to determine appropriate training parameters. Many rely on unsupervised trial-and-error approaches or generic exercise routines obtained from informal sources. Although personal trainers can provide individualized guidance, professional supervision is often limited by disproportionate trainer-to-member ratios, particularly in small or resource-constrained fitness centers. This situation creates a significant gap between the need for personalized training guidance and the availability of expert knowledge. The rapid development of artificial intelligence (AI) has introduced new opportunities to address such gaps through knowledge-based systems (Luik et al., 2025). Expert systems, as a branch of AI, are designed to replicate the decision-making processes of human experts by encoding domain knowledge into rule-based structures (Ravi et al., 2025).

Previous studies have demonstrated the application of expert systems in health-related domains such as medical diagnosis, nutrition planning, and rehabilitation guidance (Coman et al., 2024; Hassan & Elagamy, 2025; Li et al., 2025; Mileva & Zaidell, 2022; Stefanidis et al., 2022; Swami et al., 2025; Torre et al., 2025). However, most existing fitness-related applications primarily focus on body mass index (BMI) classification, calorie tracking, or general workout recommendations without structured reasoning mechanisms. Moreover, current mobile fitness applications rarely implement rule-based inference methods combined with heuristic search strategies to optimize recommendation accuracy and computational efficiency. This limitation indicates a research gap in the development of intelligent, rule-based fitness recommendation systems that integrate structured expert knowledge with efficient search mechanisms, particularly for resistance training customization based on anthropometric parameters. Additionally, there is limited research on implementing such systems in lightweight mobile environments suitable for resource-constrained devices.

To address this gap, this study proposes a mobile-based expert system for arm muscle training recommendations that integrates forward chaining and best-first search. Forward chaining is a data-driven inference mechanism that derives conclusions from known user parameters (e.g., height and weight) by matching them to if–then rules stored in the knowledge base (Babu et al., 2025; Zahra et al., 2025). This method ensures logical consistency and transparency in the recommendation process. To enhance computational efficiency and reduce unnecessary rule exploration, the best-first search algorithm is incorporated to prioritize the most relevant rule branches using heuristic evaluation (Baz et al., 2022; Rathnayake et al., 2021). The combination of these two methods enables both systematic reasoning and optimized search performance within the rule space.

The novelty of this research lies in three primary aspects. First, it integrates rule-based reasoning (forward chaining) with heuristic search (best-first search) in a unified framework for personalized resistance training recommendation. Second, it formalizes expert knowledge in arm muscle training into a structured knowledge base that translates professional fitness guidance into computational logic. Third, it implements the proposed system in a mobile environment using java 2 micro edition (J2ME), with MySQL as the relational database management system and PHP as the server-side communication interface, thereby demonstrating the feasibility of deploying intelligent expert systems on resource-limited devices. Therefore, the objective of this study is to design and develop a mobile-based expert system capable of generating personalized arm muscle training recommendations, including exercise type, equipment selection, number of sets, repetitions, and suggested lifting load. The proposed system is expected to contribute to the field of AI-based health technology by providing an intelligent, accessible, and computationally efficient solution for beginner-level resistance training guidance.

Method

This research adopts a software development approach using the waterfall model as the system development life cycle (SDLC). The Waterfall model was selected for its structured, sequential, and documentation-driven characteristics, which ensure that each development phase is completed systematically before proceeding to the next. This approach is particularly suitable for expert system development, where requirements and domain knowledge must be clearly defined and validated prior to implementation. The development process consists of requirements analysis, system design, implementation, testing, validation, and maintenance.

The first phase was requirements analysis, which served as the foundation for system development. This stage involved identifying both functional and non-functional requirements of the application. Functional requirements include user input of anthropometric parameters (height and weight), rule-based processing using inference mechanisms, and generation of arm muscle training recommendations, including exercise type, equipment, number of sets, repetitions, and suggested lifting load. Non-functional requirements include compatibility with Java-based mobile devices, efficient response time, and user-friendly interface design. In addition, a literature review was conducted to establish the study's theoretical framework. The review covered expert system architecture, forward chaining inference method, best-first search algorithm, and fundamental principles of resistance training. Relevant sources were obtained from books, peer-reviewed journals, and reputable scientific publications.

Knowledge acquisition was conducted through structured interviews with a professional fitness instructor, Mr. Rosdiana Bunardi Boen, the owner of Catherine & Erico Fitness Studio. The interviews aimed to extract domain-specific knowledge regarding the correlation between body posture (height and weight) and weightlifting capacity, classification of training intensity, and appropriate arm exercises based on individual characteristics. The acquired knowledge was then formalized into production rules using if–then statements, which formed the core of the system's knowledge base.

Following the requirements definition, the system design phase was conducted. The system adopts a client–server architecture in which the mobile device functions as the client interface, while the server handles data processing and database management. The knowledge base was structured as a set of rule-based representations, and the inference engine was designed to use forward chaining to derive conclusions from user input data. To optimize rule exploration and improve computational efficiency, the best-first search algorithm was integrated to prioritize the most relevant rule branches based on heuristic evaluation. Database design was developed using entity relationship diagrams (ERD) and logical record structures (LRS), with main tables including exercise, target, conclusion, direction, and dictionary. The user interface was designed using system flowcharts and mobile interface mockups to ensure intuitive, user-friendly interaction.

In the implementation phase, the system design was translated into program code. The client-side application was developed using java 2 micro edition (J2ME) to ensure compatibility with resource-constrained mobile devices. The server-side application was implemented in PHP to handle user requests and communicate with the MySQL database, which serves as the relational database management system for storing expert rules and user data. Communication between the mobile application and the server is conducted via the HTTP protocol over GPRS/3G networks.

System evaluation was conducted through integration and testing phases. Black-box testing was employed to verify the correctness of the input-output functionality without examining the internal program structure. The testing focused on validating data input processing, rule execution, and the accuracy of generated recommendations. Furthermore, the system's conclusions were compared with the expert instructor's manual recommendations to assess the validity and consistency of the inference results. This validation process ensured that the expert system's output aligned with professional judgment.

Finally, the maintenance phase was carried out after deployment to ensure long-term system reliability and relevance. Maintenance activities include debugging and correcting potential errors, optimizing performance, and updating the knowledge base by adding new exercise variations in accordance with developments in fitness science. This phase ensures that the application remains accurate, functional, and adaptable to future requirements.

Results and discussion

The development of the mobile-based expert system for arm muscle training successfully produced a functional application capable of generating personalized exercise recommendations based on user anthropometric data. The system integrates a structured knowledge base, a forward-chaining inference engine, and a best-first search optimization mechanism within client–server architecture. The implementation demonstrates that rule-based artificial intelligence can operate effectively in a lightweight mobile environment.

The database design was implemented using a normalized relational structure derived from the entity relationship diagram (ERD) and logical record structure (LRS). The primary tables, admin, dictionary, exercise, target, and conclusion, were successfully created and interconnected. The many-to-many relationship between the exercise and target tables accurately represents real training scenarios, where a single exercise may target multiple muscle groups, and different exercises may train each muscle group. The conclusion table serves as the primary rule repository, establishing associations between user parameters (gender, height, and weight) and predefined exercise packages. The system's structure allows adding new rules without altering the core database framework.

The ERD (Figure 1) illustrates the main entities involved in the system, including admin, dictionary, exercise, target, and conclusion. These entities represent core components, including user authentication, technical terminology, types of arm muscle exercises, targeted muscle groups, and the recommendation rules that link physical parameters to exercise suggestions. The relationships between these entities depict how the system organizes and connects various pieces of knowledge to deliver personalized exercise recommendations.

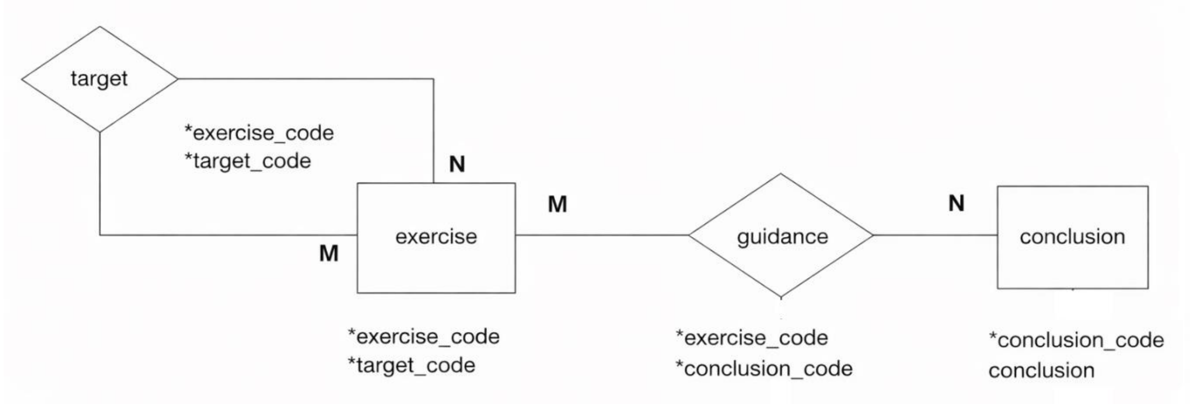

Figure 1 entity relationship diagram (ERD) of the arm muscle expert system

The database comprises several key tables derived from the ERD. The admin table manages administrator authentication data to ensure secure access for knowledge management. The dictionary table contains technical fitness terms and their definitions, providing users with clear explanations of pertinent concepts. The exercise table contains a catalog of arm muscle exercises, while the target table records the specific muscles targeted by each exercise, such as the biceps, triceps, and forearms. Notably, the relationship between exercises and target muscles is many-to-many: a single exercise can engage multiple muscle groups, and multiple exercises can target each muscle group.

At the core of the system is the conclusion table, which functions as the primary rule repository. It connects the user's physical parameters, such as height and weight, with corresponding exercise recommendations. This table establishes many-to-many relationships with the Exercise table, enabling the system to generate tailored advice based on individual user profiles. The overall database design, therefore, supports flexibility and extensibility, allowing new rules and knowledge to be added without disrupting the existing structure. The database design employs a systematic and normalized approach to organize knowledge within the arm muscle expert system. By utilizing ERD and LRS methodologies, the system achieves efficient data storage, minimizes redundancy, and ensures ease of maintenance and scalability. This foundation allows the expert system to effectively manage and deliver personalized exercise guidance based on scientific rules and user-specific parameters.

The LRS illustrates a one-to-many cardinality between the exercise and target tables, alongside a composite relationship used to derive conclusions. This complex decision-making process is effectively represented by a decision tree, which models the inference logic by mapping user inputs into distinct decision branches. Figure 2 depicts the decision tree for determining exercise patterns based on user-specific attributes. The system's inference flow begins by receiving the user's gender (male or female) as input. Subsequently, the tree evaluates the user's height and categorizes it as short, medium, or tall. Following this, the system assesses the user's weight and classifies it as thin, ideal, or overweight. By analyzing the combined values of these three variables, gender, height, and weight, the system navigates through the decision branches until it reaches a leaf node representing the final recommendation, identified by a unique solution id or exercise package.

For example, one of the decision rules can be formulated as follows: if gender = 'male' and height > 170 cm and weight > 75 kg, then the user falls under the 'large body' category, and the corresponding exercise recommendation is 'heavy duty,' characterized by maximum load with low repetitions (6–8 times). This structured inference mechanism ensures personalized exercise guidance by systematically evaluating key physical parameters. The use of a decision tree not only simplifies rule-based logic but also enhances the system's ability to deliver accurate, tailored exercise recommendations based on individual user profiles.

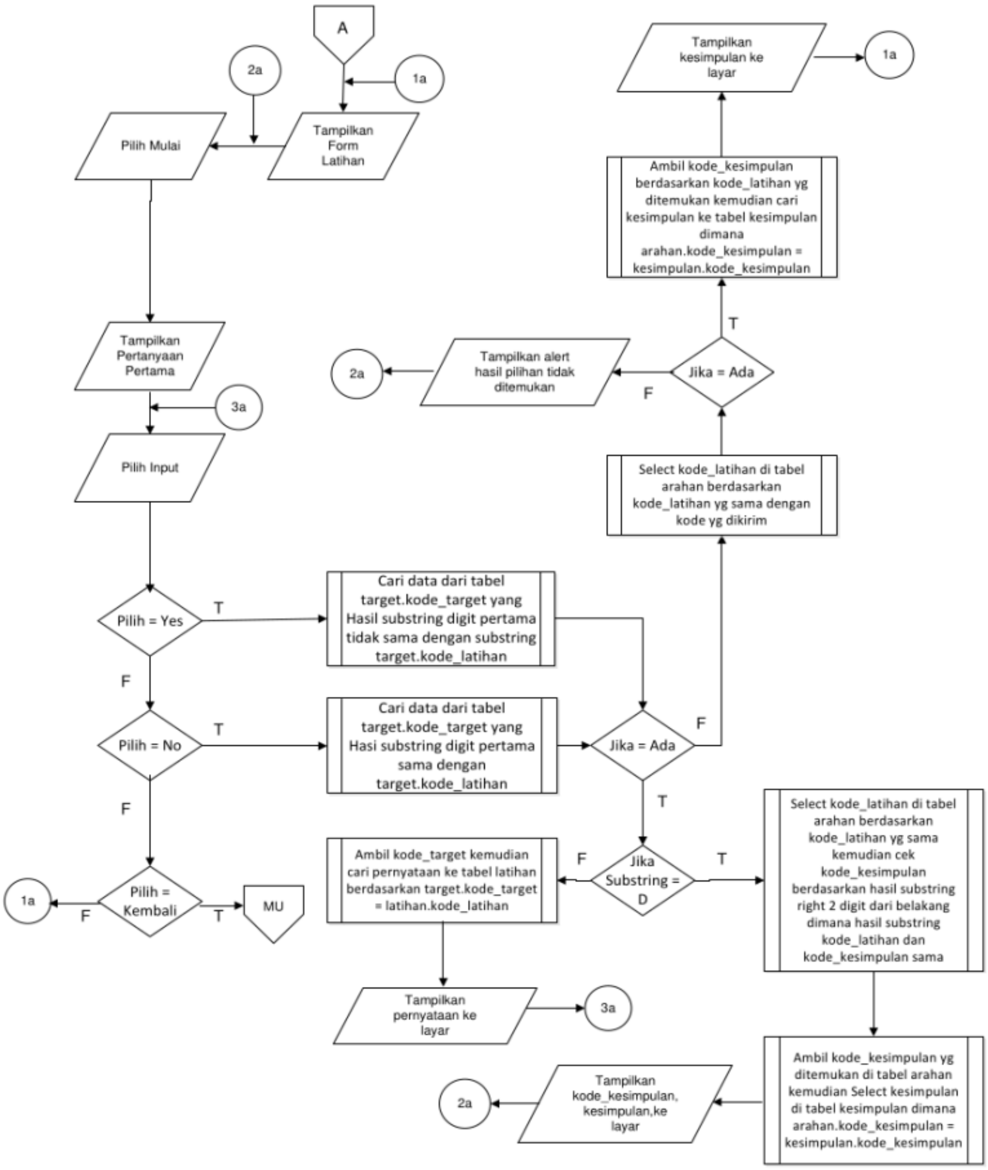

Figure 2 decision tree for determining exercise patterns

The inference process operates in two stages. First, the forward chaining method processes user inputs as initial facts and evaluates if–then rules stored in the knowledge base. The system systematically matches input data against rule conditions until a valid recommendation is produced. Second, the best-first search algorithm prioritizes rule paths that are heuristically closer to a final solution, thereby reducing unnecessary rule exploration. Testing results show that the system generates recommendations with a fast response time and consistent logical reasoning.

The application features a simple interface that accounts for the limitations of mobile device screens. Figure 3 illustrates the main menu page of the expert system application, which features a simple, user-friendly interface to accommodate the limitations of mobile device screens. This page serves as the primary gateway for users when accessing the application. At the top of the screen, the heading “selamat datang di sistem pakar” (welcome to the expert system) clearly indicates that users have entered the system’s main interface. The layout is organized in a vertical menu structure, making it easy for users to navigate the available features.

The menu options presented include “mulai identifikasi” (start identification), which enables users to begin the consultation or problem identification process; “kamus” (dictionary), which provides definitions of relevant terms; “tentang program” (about the program), which contains general information about the application; “informasi” (information), which offers additional related content; “petunjuk pemakaian aplikasi” (user guide), which explains how to operate the application; and “login admin,” which is intended for administrators to manage system data. An icon accompanies each menu item to enhance visual recognition and usability. At the bottom of the screen, a “keluar” (exit) option lets users close the application. Overall, the main menu interface is structured to ensure clarity, accessibility, and ease of navigation for users.

Figure 3 main application menu display

Figure 4 presents the consultation page (data input) of the expert system application. This page is designed to collect essential user information needed for identification or consultation. At the top of the interface, the section title “identifikasi” (identification) indicates that the user has entered the consultation stage of the system. One of the primary input fields displayed is “kode latihan” (training code), which is automatically populated with “A001,” suggesting that the system assigns or verifies a specific consultation or case code before proceeding.

Below the code field, the system displays a question, “apakah anda pria?” (are you male?), which represents the beginning of the data collection process. This structured questioning format allows the system to gather relevant physical or demographic information from the user in a step-by-step manner. The interface layout remains simple and uncluttered to ensure readability and ease of interaction on mobile devices. Additionally, input validation mechanisms are implemented to prevent users from submitting blank or improperly formatted data, thereby ensuring the accuracy and reliability of the consultation results. Navigation options such as “batal” (cancel) and “menu” are provided at the bottom of the screen, allowing users to either exit the current process or return to the main menu. Overall, this page demonstrates a clear, systematic approach to user data entry in the expert system application.

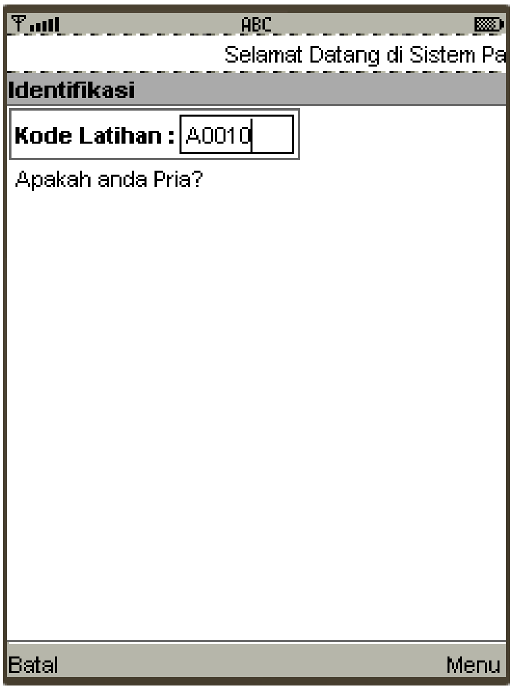

Figure 4 consultation data input display

Figure 5 illustrates the expert system application’s diagnosis results page, which appears after the user presses the “process” button. This page presents the consultation outcomes in a structured, comprehensive format. At the top of the interface, the section titled “kemungkinan pola latihan” (possible training patterns) indicates that the system has analyzed the user’s input data and generated exercise recommendations tailored to the identified body condition. The results display includes a body condition analysis, for example, classifying the user’s physique into a specific category, such as “athletic.” Based on this classification, the system provides a list of recommended exercises, such as triceps extension, triceps pushdown, and triceps kickback. Each exercise entry includes detailed training parameters, including the type of equipment used (e.g., dumbbells or one-arm cable), the number of sets, the number of repetitions per set, and the suggested weight range. This detailed breakdown ensures users receive clear, practical guidance for implementing the recommended training program. The layout is organized in a scrollable list to accommodate multiple exercise options while maintaining readability on a mobile device. Overall, the diagnosis results page demonstrates how the expert system translates user input into personalized exercise recommendations, providing both analytical feedback and actionable training instructions in a clear, systematic manner.

Black box testing was conducted to evaluate the functional correctness of the proposed mobile-based expert system for arm muscle training recommendations. The testing focused on verifying that each system module operates according to the specified functional requirements, without examining its internal program structure. The evaluation covered user authentication, data input validation, inference processing, database interaction, and result presentation (Table 1).

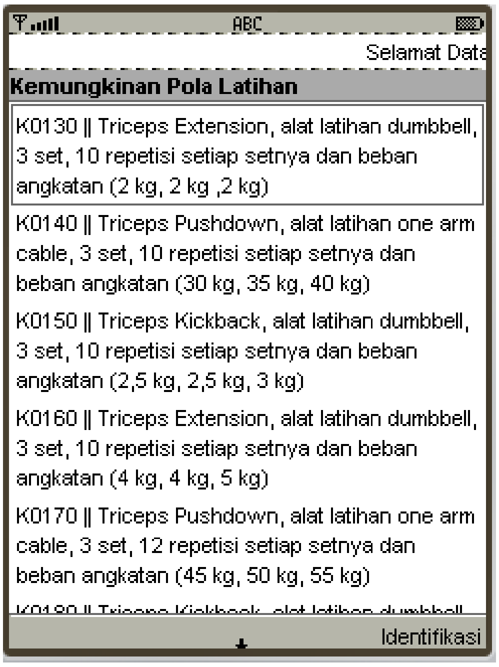

Figure 5 diagnosis result page display

Table 1 black box testing results

Nu	Module tested	Test scenario	Input	Expected output	Actual output	Status
1	Admin login	Login using valid credentials	Correct username and password	Admin dashboard is displayed	Admin dashboard displayed	Pass
2	Admin login	Login using incorrect password	Correct username, incorrect password	Error message is displayed	“Login failed” message displayed	Pass
3	User registration	Complete data input	Name, gender, height, weight provided	Data stored in database	Data successfully stored	Pass
4	User registration	Incomplete data input	One or more fields left blank	System rejects input and displays warning	“Incomplete data” message displayed	Pass
5	Consultation – gender input	Select gender	Male	System proceeds to height input	Height input page displayed	Pass
6	Consultation – height input	Valid height input	175 cm	System proceeds to weight input	Weight input page displayed	Pass
7	Consultation – weight input	Valid weight input	80 kg	System processes data and generates result	Diagnosis result page displayed	Pass

Nu	Module tested	Test scenario	Input	Expected output	Actual output	Status
8	Height validation	Non-numeric height input	"abc"	System rejects invalid input	Error message displayed	Pass
9	Weight validation	Negative weight value	-70 kg	System rejects invalid input	Error message displayed	Pass
10	Inference process	Valid parameter combination	Male, 175 cm, 80 kg	"Large Body" category with Heavy Duty training (6–8 reps)	Recommendation matches rule base	Pass
11	Inference process	Alternative valid combination	Female, 160 cm, 50 kg	"Slim Body" category with Moderate Load (10–12 reps)	Recommendation matches rule base	Pass
12	Rule execution	Undefined parameter combination	Input outside predefined rules	System displays notification	"Data not found" message displayed	Pass
13	Result display	Display training recommendation	Process completed	Body classification, exercises, sets, repetitions, and load displayed	All components displayed correctly	Pass
14	Dictionary module	Select fitness terminology	Select "Triceps"	Definition displayed	Definition displayed correctly	Pass
15	Navigation control	Cancel consultation	Press "Cancel" button	Return to main menu	Main menu displayed	Pass
16	Exit function	Exit application	Press "Exit" button	Application closes	Application closed successfully	Pass

Table 1 shows that the system satisfies all predefined functional requirements. Input validation mechanisms successfully prevented incomplete and invalid data from being processed by the inference engine. The forward chaining inference mechanism, optimized by the best-first search strategy, consistently generated recommendations that aligned with the rules stored in the knowledge base. Furthermore, the system demonstrated stable interaction between the mobile client (a J2ME-based application) and the server-side components (PHP and a MySQL database). The response time during rule execution and result generation remained within acceptable limits for mobile environments.

System testing was conducted to verify input validation, rule execution, and output accuracy. All application modules, including login, registration, consultation, and result generation, were implemented in accordance with the functional specifications. Input validation successfully prevented incomplete or invalid data from being processed. Furthermore, system-generated recommendations were compared with manual evaluations from the professional fitness instructor involved in the knowledge acquisition phase. The results showed strong consistency between the system output and expert judgment.

From a user interface perspective, the application operates effectively within the constraints of java-based mobile devices. The main menu structure (login, register, consultation, dictionary, and help) enables straightforward navigation. The consultation page allows users to input physical data clearly, and the diagnosis results page presents body classification, recommended exercises, and detailed sets and repetitions in a structured format. Overall, the system achieved its objective of delivering personalized guidance for arm muscle training via a mobile platform.

Discussion

The results of this study demonstrate that integrating forward chaining and best-first search within a mobile-based expert system provides a structured, computationally efficient solution for personalized resistance training recommendations. From a theoretical perspective, forward chaining aligns with the classical expert system architecture introduced in early artificial intelligence systems such as MYCIN, which used rule-based reasoning to replicate expert decision-making processes in medical diagnosis (Khan et al., 2025). Similar to MYCIN, the proposed system relies on explicit if–then production rules derived from domain experts, ensuring that the reasoning process remains transparent, explainable, and logically traceable (Saeidnia & Nilashi, 2025; Zhang et al., 2024). This transparency is particularly important in health-related applications, where users must trust that recommendations are grounded in systematic evaluation rather than arbitrary computation.

Previous research has widely applied expert systems in healthcare domains, including disease diagnosis, nutrition planning, and rehabilitation monitoring (Coman et al., 2024; Hassan & Elagamy, 2025; Joshi et al., 2024; Petrauskas et al., 2021). These systems typically emphasize rule-based inference to ensure consistency with professional standards. However, in the context of fitness technology, many contemporary mobile applications primarily focus on calorie counting, body mass index (BMI) calculation, or generalized workout templates (Ardiansyah & Avianto, 2024). Such applications often lack a formal reasoning mechanism that systematically derives recommendations from structured knowledge bases. In contrast, this study formalizes professional fitness knowledge into computational rules. It integrates heuristic search optimization, thereby extending the methodological rigor commonly found in medical expert systems to the field of resistance training guidance.

The incorporation of the best-first search algorithm represents an important methodological contribution. Traditional rule-based systems that use pure forward chaining may become less efficient as the number of rules increases, since the engine must evaluate multiple rule paths sequentially (Borghoff et al., 2025; Liang et al., 2025). By integrating heuristic evaluation, the system prioritizes rule branches that are more likely to lead to a valid conclusion. This approach is conceptually consistent with heuristic search strategies introduced in artificial intelligence research, such as those discussed in the development of problem-solving systems, such as the general problem solver. Although the complexity of the present system is considerably lower than that of classical AI search problems, adopting best-first search demonstrates that optimization techniques can enhance performance even in relatively small rule spaces (Balogun et al., 2024). This becomes increasingly relevant as the knowledge base expands to include additional training variables.

From a resistance training science perspective, the system's recommendation logic aligns with established training principles proposed by organizations such as the American college of sports medicine (ACSM) (Bishop et al., 2025). The ACSM guidelines emphasize that training intensity, load, and repetition ranges should be adjusted according to individual characteristics and goals (Donovan & Carrothers, 2024). For example, higher loads with lower repetitions are commonly associated with strength development, while moderate loads with higher repetitions are linked to muscular endurance. The decision tree implemented in this study reflects these principles by categorizing users into body profiles and assigning corresponding intensity levels. Although simplified, this structure demonstrates consistency with foundational resistance training theory.

Compared with previous fitness-related systems, this research contributes to three key aspects. First, it moves beyond descriptive classification (e.g., BMI categorization) by implementing prescriptive rule-based reasoning that directly generates actionable exercise parameters, including sets, repetitions, and load recommendations. Second, it combines deterministic inference with heuristic optimization, improving computational efficiency compared to purely sequential rule evaluation. Third, it demonstrates feasibility in a resource-constrained mobile environment using J2ME, PHP, and MySQL. Earlier studies on mobile health (mHealth) applications often emphasize usability and accessibility but do not always incorporate formal AI-based reasoning mechanisms (Garcia et al., 2023). Therefore, this research bridges the gap between intelligent decision support systems and practical mobile deployment.

Nevertheless, compared with more recent AI-driven fitness technologies that use machine learning and data-driven personalization, the present system adopts a knowledge-based rather than a statistical learning approach. Machine learning systems can adapt dynamically based on user behavior patterns and large datasets, but they often lack interpretability. In contrast, rule-based systems such as the one developed in this study offer high interpretability and explainability, as each recommendation can be traced to explicit rules derived from expert interviews. This characteristic is particularly advantageous in early-stage or beginner-level guidance, where transparency and safety are prioritized over predictive complexity.

Despite its contributions, several limitations remain. The personalization mechanism is limited to gender, height, and weight. It does not incorporate additional determinants such as age, training experience, injury history, or specific fitness goals (e.g., hypertrophy, endurance, or rehabilitation). Prior research in exercise science emphasizes the importance of multifactorial assessment when designing individualized training programs (Wackerhage & Schoenfeld, 2021). Therefore, future development should integrate broader physiological and behavioral variables to increase recommendation precision. Furthermore, previous studies on digital coaching systems highlight the importance of multimedia guidance, such as instructional videos and motion analysis, to reduce the risk of technique-related injuries (Hooren et al., 2024). The current system, which delivers only text-based recommendations, may not fully address this need.

The discussion indicates that the proposed expert system successfully adapts classical rule-based AI methodologies to the domain of resistance training recommendation while maintaining computational efficiency through heuristic search integration. By aligning its inference logic with established exercise science principles and demonstrating feasibility in a mobile environment, this study contributes to the growing field of AI-based health technology. Future research should explore hybrid approaches that combine rule-based reasoning with adaptive learning techniques to enhance personalization, scalability, and long-term effectiveness.

Conclusions

This study successfully designed and implemented a mobile-based expert system for personalized arm muscle training recommendations by integrating forward chaining and best-first search methods within a structured rule-based framework. The system effectively translates professional fitness knowledge into computational logic, enabling users to obtain tailored exercise recommendations based on anthropometric parameters such as gender, height, and weight. The application demonstrates that classical artificial intelligence techniques can be efficiently deployed in a lightweight mobile environment using J2ME, PHP, and MySQL within a client–server architecture. System testing confirms that the inference results are logically consistent and aligned with expert judgment, while the heuristic search mechanism enhances computational efficiency. Although the current implementation is limited to basic physical parameters and text-based guidance, the findings indicate that rule-based expert systems offer a transparent, explainable, and practical solution for beginner-level resistance training support. Therefore, this research contributes to the development of AI-based health technologies by bridging expert knowledge representation, intelligent inference, and mobile accessibility in fitness recommendation systems.

This study has several limitations. The personalization mechanism is limited to gender, height, and weight, and does not consider additional important factors such as age, training experience, injury history, body composition, or specific fitness goals. The knowledge base was derived from a single expert, which may limit the recommendations' diversity and generalizability. Moreover, the system employs a purely rule-based approach without adaptive learning, resulting in static recommendations that do not adapt to user progress. The implementation in a J2ME-based mobile environment also limits multimedia integration and interactive features, as the system provides only text-based guidance. In addition, evaluation was limited to functional testing and expert validation without large-scale experimental assessment of training outcomes. Therefore, future research should incorporate more comprehensive user variables, involve multiple experts in knowledge acquisition, integrate hybrid approaches combining rule-based reasoning with machine learning for adaptive personalization, deploy the system on modern mobile platforms with multimedia and wearable integration, and conduct empirical studies to evaluate its effectiveness in improving physical performance.

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