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Fuzzy Mamdani-Based Book Recommendation System for Academic Library Services: Design, Implementation, and Evaluation

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Abstract
Purpose: This study aims to develop and evaluate a Fuzzy Mamdani based book recommendation system for the IIB Darmajaya Library to provide personalized recommendations and improve information retrieval efficiency.
Research Methodology: The system was developed through requirement analysis, design, implementation, testing, and evaluation. A Mamdani Fuzzy Inference System (FIS) was constructed using three input variables: borrowing frequency, book rating, and difficulty level, with recommendation score as the output. Twenty-seven fuzzy rules and triangular membership functions were applied. The system was implemented using PHP, Laravel, MariaDB, and JavaScript, while MATLAB was used for FIS verification.
Results: Functional testing confirmed the successful operation of all system modules, including authentication, recommendation generation, search, filtering, and preference updates. Verification results showed complete consistency between manual calculations and MATLAB outputs, with a sample input producing a recommendation score of 4.3.
Conclusions: The proposed system effectively generated personalized book recommendations and demonstrated the capability of the Mamdani method to manage uncertainty in user preferences.
Limitations: The evaluation was limited to functional testing in a controlled environment. User acceptance testing, scalability assessment, and additional recommendation variables were not examined.
Contributions: This study provides a validated Fuzzy Mamdani recommendation framework and a web based implementation model that can be adapted by academic libraries seeking intelligent recommendation services.

Keywords: *Academic Library, Book Recommendation System, Defuzzification, Fuzzy Mamdani, Fuzzy Inference System*

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1. Introduction

The rapid proliferation of information resources in academic environments has fundamentally transformed the operational demands of university libraries. As digital cataloguing technologies have

enabled libraries to expand their collections significantly, users face increasing difficulty in navigating large inventories of books, journals, and theses to locate materials relevant to their specific academic needs (Burke, 2010; Isinkaye et al., 2015). This "information overload" problem is particularly acute in developing country institutions, where library management systems may lack sophisticated search and recommendation functionalities, leaving users to rely on manual browsing strategies that are both time-consuming and inefficient (Bobadilla, Ortega, Hernando, & Gutiérrez, 2013).

Recommendation systems have emerged as a critical technological response to this challenge across numerous domains, from e-commerce to streaming media (Ricci, Rokach, & Shapira, 2015). In library science, recommendation systems serve a dual function: they reduce the cognitive burden on users seeking relevant materials while simultaneously supporting the collection utilization objectives of the institution Burke, 2010. The effectiveness of a recommendation system in the library context depends on its ability to capture the multidimensional and often subjectively expressed nature of user preferences, including factors such as academic difficulty level, thematic relevance to study programme, borrowing patterns, and peer ratings (Polatidis, Georgiadis, Pimenidis, & Mouratidis, 2017).

The IIB Darmajaya Library in Bandar Lampung, Indonesia houses a diverse collection of textbooks, reference works, journals, and student theses across multiple academic disciplines. Despite this breadth, users particularly those with limited subject knowledge or time constraints frequently experience difficulty in identifying appropriate titles from the collection. The library's existing digital catalogue (digilib IIB Darmajaya) provides basic search functionality but lacks an intelligent recommendation engine capable of synthesizing user context with collection metadata to generate personalized suggestions.

Fuzzy logic, specifically the Mamdani Fuzzy Inference System (FIS), presents a theoretically well-grounded approach to the recommendation challenge. Unlike crisp classification systems that assign books categorically to binary relevant/irrelevant categories, fuzzy logic accommodates the gradational and context-dependent nature of relevance judgements through linguistic variables and membership functions (Zadeh, 1965; Jang et al., 1997). The Mamdani FIS architecture is particularly suited to this application, given its interpretability, rule-based transparency, and capacity to integrate expert knowledge with data-driven parameter estimation (Mamdani & Assilian, 1975). Prior research has demonstrated the effectiveness of fuzzy logic in recommendation systems across adjacent domains, including hotel selection (Santoso & Dewi, 2021), game recommendation (Iskandar & Putra, 2020), and general e-library services (Hakim & Azhar, 2019), suggesting transferable design principles applicable to the library book recommendation context.

However, the existing applications of fuzzy based recommendations in Indonesian academic library contexts remain limited. Most prior studies either apply Sugeno type FIS (Widodo & Haryanto, 2018), which produces crisp outputs less interpretable by library staff, or restrict their input variable sets to fewer dimensions than the multi-criteria nature of book preference selection warrants. Furthermore, few studies have fully documented the web-based implementation pipeline from FIS design to user interface deployment, limiting the replicability of prior work.

This study addresses these gaps through the design, implementation, and evaluation of a complete Mamdani FIS-based book recommendation system integrated into a Laravel-based web application for the IIB Darmajaya Library. The system incorporates three input variables (boring frequency, book rating, and difficulty level), a 27 rule IF-THEN knowledge base, triangular membership functions, and centroid defuzzification to generate recommendation scores. The primary contributions of this research are as follows: (1) a domain-specific Mamdani FIS architecture validated against MATLAB based manual computation; (2) a full-stack web implementation architecture connecting the FIS engine with a user-facing recommendation interface; and (3) a functional evaluation demonstrating real-time, preference-responsive recommendation generation. The remainder of this paper is

structured as follows: Section 2 reviews the relevant theory and prior research; Section 3 describes the system design and methodology; Section 4 presents the implementation results and discussion; and Section 5 provides conclusions, limitations, and future research directions.

2. Literature Review

2.1 Recommendation Systems: Taxonomy and Library Applications

Recommendation systems are broadly classified into three paradigms: content-based filtering, collaborative filtering, and hybrid approaches (Isinkaye, Folajimi, & Ojokoh, 2015; Ricci, Rokach, & Shapira, 2015). Content-based filtering recommends items that share attributes with those previously valued by the user, collaborative filtering leverages behavioral similarities across users, and hybrid systems combine both strategies to mitigate individual limitations (Bobadilla, Ortega, Hernando, & Gutiérrez, 2013). In library contexts, the limited behavioral data available for individual users and the high dimensionality of content metadata make hybrid and knowledge-based approaches particularly appropriate (Burke, 2010; Lops, & Semeraro, 2011). Knowledge-based recommendations, in which domain expertise is encoded as rules mapping user requirements to item features, align naturally with fuzzy inference methodologies, given their capacity to linguistically represent imprecise knowledge (Polatidis, Georgiadis, Pimenidis, & Mouratidis, 2017).

2.2 Fuzzy Logic and the Mamdani FIS

Fuzzy logic, introduced by Zadeh (1965), extends classical binary logic to handle degrees of truth, thereby enabling the representation of concepts that resist crisp categorization. The Mamdani FIS, proposed by Mamdani and Assilian (1975), remains one of the most widely adopted fuzzy inference architectures owing to its intuitive IF-THEN rule structure and ability to incorporate human expert knowledge directly (Jang, Sun, & Mizutani, 1997; Zhao, Zhang, & Wang, 2021). The Mamdani system comprises four operational stages: (1) fuzzification, which converts crisp inputs to fuzzy membership degrees; (2) rule evaluation, which applies fuzzy operators to derive firing strengths for each rule; (3) aggregation, which combines rule outputs into a composite fuzzy set; and (4) defuzzification, which converts the composite fuzzy set to a crisp output value. The centroid (center of gravity) defuzzification method employed in this study computes the geometric center of the aggregated output fuzzy set and is recognized as the most accurate among common defuzzification methods (Zolfaghari, Shafahi, & Riahifar, 2022; Tapus, Çiftci, & Jain, 2022; Jang et al., 1997).

2.3 Prior Research on Fuzzy-Based Recommendation Systems

The application of fuzzy logic to recommendation problems has been extensively documented. Widodo and Haryanto (2018) implemented a fuzzy Sugeno based book recommendation system in a university library, achieving a 25% improvement in recommendation relevance by encoding the category, genre, and difficulty level as input parameters. However, the choice of Sugeno over Mamdani limits interpretability because Sugeno outputs are mathematical functions rather than linguistic labels. Setiawan, Rahmawati, and Nugraha (2022) applied the Mamdani FIS to book category recommendations for school libraries using reader age, difficulty level, and genre as inputs, reporting a 20% increase in user satisfaction and reduced selection ambiguity. These studies confirm the viability of the fuzzy approach but apply it to simpler, less feature-rich recommendation contexts than those in the present study (Sutisna, Basjaruddin, & Suryani, 2015; Putra, & Hasan, 2020).

In adjacent application domains, Santoso and Dewi (2021) applied the Mamdani FIS to hotel recommendations based on facility quality, price, and location, achieving a 33% improvement in recommendation relevance. Hakim and Azhar (2019) implemented a fuzzy based e-library recommendation system considering user age, book category, and difficulty level, reporting 26% increased user satisfaction. Iskandar and Putra (2020) applied the Mamdani FIS to game recommendations, demonstrating the generalizability of the method across recommendation domains. Collectively, these studies establish a consistent pattern of Mamdani FIS effectiveness in personalized recommendation tasks involving uncertain multi-criteria user preferences (Sarjanako, & Utami, 2017; Chen, & Pu, 2012).

In the Indonesian academic computing context, Arfida and Saputra (2017) documented a multimedia-based fuzzy logic learning application that demonstrated the pedagogical tractability of fuzzy concepts. Yulmaini (2015) applied Mamdani FIS to student academic specialisation selection, while Sulyono, Ridwan, and Purnama (2022) employed AI based algorithms for academic research scheme recommendation, demonstrating the relevance of intelligent recommendation in higher education institutional contexts (Peska & Vojtas, 2017).

2.4 Identified Research Gaps

A synthesis of the literature reveals three primary gaps addressed in this study. First, existing fuzzy-based library recommendation systems in Indonesia are either limited to the Sugeno FIS (limiting interpretability) or restrict input dimensionality to fewer than three variables, failing to capture the full complexity of academic book preference. Second, few studies have documented the end-to-end integration of a Mamdani FIS engine with a web-based application stack, limiting the replicability of prior implementations. Third, the specific context of Indonesian private university libraries characterized by mixed undergraduate populations spanning multiple study programmes has not been addressed as a distinct design context warranting customized FIS parametrization.

2.5 Theoretical Framework

This study is grounded at the intersection of two theoretical traditions. From the fuzzy systems perspective, the Mamdani FIS framework provides a formalized architecture for translating uncertain, linguistically expressed user preferences into crisp recommendation scores (Mamdani & Assilian, 1975; Zadeh, 1965). From an information retrieval perspective, the system instantiates a knowledge-based filtering paradigm in which domain-expert-derived IF-THEN rules mediate between user contextual variables and book suitability scores (Burke, 2010; Ricci et al., 2015). The integration of these frameworks produces a recommendation architecture that is simultaneously mathematically rigorous and intuitively interpretable by non-specialist, library administrators.

3. Research Methodology

3.1 Research Design and Setting

This research adopted a Design Science Research (DSR) methodology (Hevner, March, Park, & Ram, 2004), structured around the iterative design, construction, and evaluation of an information technology artifact: the Fuzzy Mamdani book recommendation system. The study was conducted at the IIB Darmajaya Library, Bandar Lampung, Indonesia, over one to three months. Data for system parameterization were obtained from the library's existing digital catalogue system (Digilib IIB Darmajaya).

3.2 System Architecture

The system architecture comprises three layers. The presentation layer was built using PHP with the Laravel framework (v8.x) and JavaScript for responsive, interactive user interface elements. The application logic layer implements the Mamdani FIS engine and processes user preference inputs through a fuzzification inference defuzzification pipeline. The data layer employs MariaDB for book collection metadata and user profile storage, which is managed through phpMyAdmin. MATLAB r2016a was employed independently for FIS prototyping, membership function visualization, and computational verification prior to the web-system implementation.

3.3 Fuzzy Inference System Design

3.3.1 Input Variables and Membership Functions

Three input linguistic variables were defined, each partitioned into three fuzzy sets with triangular membership functions:

Table 1. Input Variable Definitions and Membership Function Parameters

Variable	Linguistic Term	Range	Parameters (a, b, c)	Type
Borrowing Frequency	Few	[0, 10]	(0, 0, 10)	Triangular

Variable	Linguistic Term	Range	Parameters (a, b, c)	Type
	Moderate	[0, 10]	(0, 5, 10)	Triangular
	Many	[0, 10]	(5, 10, 10)	Triangular
Book Rating	Low	[0, 5]	(0, 0, 3)	Triangular
	Moderate	[0, 5]	(0, 2.5, 5)	Triangular
	High	[0, 5]	(2, 5, 5)	Triangular
Difficulty Level	Easy	[1, 4]	(1, 1, 2.5)	Triangular
	Moderate	[1, 4]	(1, 2.5, 4)	Triangular
	Difficult	[1, 4]	(2.5, 4, 4)	Triangular

Table 1 presents the input variables and membership function parameters used in the fuzzy recommendation system. Three input variables were defined, namely Borrowing Frequency, Book Rating, and Difficulty Level, each represented by three linguistic terms using triangular membership functions. Borrowing Frequency was categorized into Few, Moderate, and Many within a range of 0–10. Book Rating was classified as Low, Moderate, and High over a range of 0–5, while Difficulty Level was divided into Easy, Moderate, and Difficult within a range of 1–4. The triangular membership functions were selected due to their simplicity, computational efficiency, and suitability for representing gradual transitions between linguistic categories. The output variable, Recommendation Score, was defined on a range of 0–5 and consisted of three linguistic terms: Low, Moderate, and High, which were also modeled using triangular membership functions. These fuzzy sets enable the system to transform numerical input values into linguistic representations and support the inference process for generating personalized book recommendation scores

3.3.2 Rule Base Construction

A complete rule base of 27 IF-THEN rules was constructed to cover all combinations of the three input linguistic variable states (3 × 3 × 3 = 27 rules). Rules were formulated by a domain expert (library staff and faculty advisor) following the logical principle that books with higher borrowing frequency and higher ratings should generally receive higher recommendation scores, while the difficulty level provides a contextual modifier reflecting the match between book complexity and user need. The operator (minimum T-norm) was applied to the rule antecedent conjunction. The three representative rules are as follows:

1. R1: If borrowing frequency is few and book rating is low and difficulty level is easy, then the recommendation score is low.
2. R3: If borrowing frequency is few and book rating is low and difficulty level is difficult, then the recommendation score is high.
3. R14: If borrowing frequency is moderate and book rating is moderate and difficulty level is moderate, then the recommendation score is moderate.

The complete rule set was encoded in MATLAB Fuzzy Logic Toolbox for verification and subsequently implemented programmatically in the Laravel application's backend.

3.3.3 Inference and Defuzzification

The Mamdani min-max inference method was applied, and the firing strength (α) for each rule was computed as the minimum of its antecedent membership degrees (min T-norm). The output fuzzy sets from all the active rules were aggregated using the maximum operator. Defuzzification employed the centroid (center of gravity) method.

$$z^* = \int \mu(z) \cdot z \cdot dz \,/\, \int \mu(z) \cdot dz$$

For the sample input case (Borrowing Frequency = 6, Rating = 2, Level = 3), the firing strengths were: $\alpha 1 = \min(0.8, 1, 0) = 0$, $\alpha 2 = \min(0.8, 1, 0) = 0$, and $\alpha 3 = \min(0.8, 1, 1) = 0.8$. The

defuzzification computation yielded moment M1 = 2.60266, M2 = 1.536, areas A1 = 0.64, A2 = 0.32, and the final crisp output z* = (2.60266 + 1.536) / (0.64 + 0.32) = 4.13866 / 0.96 = 4.3.

3.4 System Development and Testing

The web application was developed following an iterative agile approach with three development sprints covering (1) database schema design and CRUD operations for book metadata, (2) FIS engine implementation and integration with the database, and (3) user interface development and system integration testing. Functional testing employed black-box test cases covering all primary user journeys: registration, login, preference input, recommendation display, search, filtering, and preference updates. MATLAB based verification compared manual FIS calculations with the PHP implemented FIS engine to validate the computational accuracy.

The adoption of an iterative agile development approach contributed to the flexibility and incremental refinement of the system throughout the development process. By dividing the project into multiple development sprints, each major component of the system could be implemented, tested, and improved before progressing to subsequent stages. This approach reduced integration risks and enabled early identification of functional issues, particularly during the implementation of the fuzzy inference engine and its interaction with the database layer. As a result, the development process facilitated a more stable and maintainable application architecture while ensuring that core functionalities were validated continuously.

Furthermore, the combination of functional testing and MATLAB-based verification provided a comprehensive evaluation framework for both software reliability and computational correctness. Black-box testing confirmed that user-facing features operated according to their specifications, while the comparison between manual calculations, MATLAB simulations, and PHP-generated outputs ensured the accuracy of the fuzzy inference mechanism. The use of multiple verification methods strengthens the credibility of the system and demonstrates that the recommendation results are not only operationally functional but also mathematically consistent. Such a dual validation strategy is particularly important for intelligent recommendation systems, where both usability and algorithmic accuracy directly influence user trust and system effectiveness.

4. Results and Discussions

4.1 FIS Verification and Computational Accuracy

MATLAB r2016a verification of the implemented FIS demonstrated complete consistency between the manual calculations and the automated system. For the benchmark input (Borrowing Frequency= 6, Rating = 2, Level = 3), both the manual centroid computation and the MATLAB Rule Viewer produced a recommendation score of 4.3, confirming the accuracy of the membership function definitions, rule base encoding, and defuzzification implementation. This numerical consistency validates the fidelity of the PHP-based FIS engine to the MATLAB prototype and provides confidence in the reliability of the recommendation outputs of the system.

The membership degree calculations for the benchmark case clearly illustrate the FIS operation. The borrowing frequency value of 6 activated two fuzzy sets: μ_1_low[6] = (10−6)/(10−5) = 0.8 and μ_1_moderate[6] = (6−5)/(10−5) = 0.2, whereas μ_1_many[6] = 0. The rating value of 2 exclusively activates the low rating set: μ_2_low[2] = 1, μ_2_moderate[2] = 0, μ_2_high[2] = 0. The difficulty level of 3 exclusively activated the difficult set: μ_3_difficult[3] = 1, μ_3_moderate[3] = 0, and μ_3_easy[3] = 0. These membership degrees determined the firing strength of Rule R3 as $\alpha 3 = \min(0.8, 1, 1) = 0.8$, which drove the recommendation towards the high output set, yielding z* = 4.3 on the [0, 5] scale.

4.2 Functional Testing Results

Black-box functional testing confirmed the successful operation of the proposed model across all eight primary test scenarios. Table 2 summarizes the test results.

Table 2. Black-Box Functional Testing Summary

No.	Test Scenario	Expected Outcome	Actual Result	Status
1	User registration with valid credentials	Account created; redirect to login page	As expected	✓ Pass
2	User login with correct credentials	Authenticated session; redirect to home	As expected	✓ Pass
3	Book recommendation based on user preferences	Relevant books displayed ranked by recommendation score	As expected	✓ Pass
4	Search function with valid book title	Matching books returned in results	As expected	✓ Pass
5	Filter by category and difficulty level	Filtered results consistent with selected criteria	As expected	✓ Pass
6	Update user preference parameters	Recommendation list refreshes to reflect updated preferences	As expected	✓ Pass
7	Login with invalid credentials	Error message displayed; access denied	As expected	✓ Pass
8	FIS output consistency check (input [6,2,3])	Recommendation score = 4.3	Score = 4.3	✓ Pass

Table 2 summarizes the results of the black-box functional testing conducted to evaluate the correctness and completeness of the book recommendation system. Eight test scenarios covering key system functionalities, including user registration, authentication, recommendation generation, search operations, filtering mechanisms, preference updates, and recommendation score validation, were executed successfully. All test cases produced outcomes consistent with the expected results, indicating that the system functions reliably across its primary user interaction pathways. In particular, the recommendation module successfully generated ranked book suggestions based on user preferences, while the search and filtering features returned results that accurately reflected the selected criteria (Ricci et al., 2015).

The results also confirm the computational correctness of the fuzzy inference implementation. As shown in Test Scenario 8, the recommendation score generated by the system for the sample input vector [6, 2, 3] matched the expected value of 4.3, validating the accuracy of the fuzzification, inference, and defuzzification processes. Furthermore, Test Scenario 6 demonstrated that modifications to user preference parameters immediately triggered updates to the recommendation results, highlighting the system's real-time responsiveness. This capability is particularly important in recommendation environments because it allows users to iteratively adjust their preferences and instantly observe the impact on suggested books, thereby improving personalization, user engagement, and overall decision support effectiveness.

4.3 System Interface and User Experience Design

The Laravel-based web interface presents recommendations in a card-based grid layout that displays book cover thumbnails, titles, authors, and category tags. The design prioritizes visual clarity and navigational simplicity, consistent with usability guidelines for academic library information systems (Nielsen, 1994). The interface's responsiveness, achieved through JavaScript driven dynamic content updates, enables seamless preference adjustment without full page reloads, reducing interaction latency. Navigation menus provide access to the home recommendation view, full book catalogue, repository section, and user feedback functionality (Davis, 1989).

The interface design also supports efficient information exploration by presenting essential book metadata in a concise and visually organized format. The use of cover images, author information, and category labels allows users to quickly assess the relevance of recommended books before accessing more detailed descriptions. This approach reduces cognitive load during the search process and facilitates faster decision-making, particularly for users who need to navigate large collections within

limited time. Such visual presentation strategies are widely recognized as important factors in improving user engagement and satisfaction in digital library systems.

Moreover, the responsive nature of the interface enhances accessibility across different devices and usage contexts. Dynamic content updates allow recommendation results to be refreshed instantly when user preferences change, creating a more interactive and personalized experience. The availability of dedicated sections for book catalogues, institutional repositories, and user feedback further supports a comprehensive information retrieval environment. By integrating recommendation services with broader library resources, the system encourages continuous user interaction and promotes more effective utilization of academic information resources available within the library ecosystem.

4.4 Comparative Analysis with Prior Systems

Compared to prior fuzzy-based library recommendation systems, the present implementation offers several distinguishing characteristics. Compared to Widodo and Haryanto (2018), who employed Sugeno FIS, the Mamdani architecture used in this study produces linguistically interpretable output labels (Rendah/Sedang/Tinggi) that are more readily communicable to library staff and users who are unfamiliar with fuzzy mathematics (Zhang, Lin, Liu, Wu, Zhang, & Lu, 2014). Compared with Setiawan et al. (2022), who targeted school library users, the input variable set of the present system specifically, the inclusion of actual borrowing frequency alongside subjective ratings and difficulty introduces an objective usage data dimension absent from purely preference-based approaches. The full-stack web implementation documented in this study also provides greater deployment details than most prior publications, enhancing methodological replicability.

In addition to its methodological differences, the proposed system demonstrates the practical advantages of integrating fuzzy inference techniques within a modern web-based architecture. Unlike many earlier studies that focused primarily on algorithmic design or simulation environments, this implementation combines recommendation logic with user authentication, search, filtering, and real-time preference adjustment features in a unified platform. This integration enhances the applicability of the system in real library operations by enabling seamless interaction between recommendation services and routine information retrieval activities. Consequently, the system not only functions as a decision-support tool but also contributes to improving the overall user experience in accessing library resources.

Furthermore, the incorporation of both objective and subjective input variables provides a more balanced representation of user preferences than approaches relying solely on explicit ratings or predefined interests. Borrowing frequency reflects actual user behavior, while rating and difficulty level capture individual perceptions and reading preferences. This combination aligns with contemporary recommender-system research, which emphasizes the importance of integrating behavioral and preference-based data to improve recommendation relevance and personalization. As academic libraries continue to expand their digital and physical collections, such hybrid preference modeling approaches may offer a practical solution for supporting efficient resource discovery and encouraging greater utilization of library services.

4.5 Limitations of the Current Implementation

The limitations of the current implementation must be acknowledged. First, the 27 rule knowledge base was constructed based on domain expert elicitation rather than empirical optimization, and the rules were not validated against actual user preference data through user acceptance testing. Second, the system currently incorporates three input variables; the exclusion of potentially relevant dimensions such as academic study programme alignment, author reputation, and recency of publication may constrain the recommendation quality for users with highly specific disciplinary needs. Third, the system's performance under high concurrency conditions, where multiple users simultaneously submit recommendation requests, was not assessed, leaving scalability questions unresolved. Fourth, the membership function parameter values were set based on expert judgement and the range of available data values; a data-driven approach to membership function optimization

may yield improved recommendation accuracy in the future (Venkatesh, Thong, & Xu, 2022; Isinkaye, Folajimi, & Ojokoh, 2015).

Furthermore, the evaluation conducted in this study focused primarily on functional correctness rather than recommendation effectiveness from the end-user perspective. Although the system successfully generated recommendations according to the predefined fuzzy rules, no quantitative assessment was performed to measure recommendation relevance, user satisfaction, perceived usefulness, or recommendation accuracy using established recommender-system metrics. Consequently, it remains unclear to what extent the generated recommendations align with actual user reading interests and information needs. Future studies should incorporate user-centered evaluation approaches, including surveys, usability assessments, and recommendation quality metrics, to provide a more comprehensive understanding of the system's practical effectiveness in real library environments.

Another limitation concerns the static nature of the recommendation mechanism. The current system relies on predefined fuzzy rules and does not automatically adapt to evolving user behaviors, borrowing patterns, or changes in library collections over time. As user preferences and reading trends may shift across academic semesters and disciplines, a fixed rule-based approach may gradually lose its effectiveness. Integrating adaptive learning capabilities, such as hybrid recommendation techniques that combine fuzzy logic with machine learning or collaborative filtering methods, could enable the system to continuously refine its recommendations based on accumulated user interaction data. Such enhancements would improve personalization quality and increase the long-term sustainability of the recommendation system in dynamic academic library settings.

4.6 Discussions

The findings demonstrate that the Mamdani Fuzzy Inference System (FIS) can effectively support personalized book recommendation processes within a web-based library environment. The perfect consistency between manual calculations, MATLAB verification, and the PHP-implemented system confirms the computational validity of the proposed approach. This result indicates that the fuzzification, inference, and defuzzification procedures were correctly translated from the prototype stage into the operational application. The successful verification process strengthens confidence in the reliability of the recommendation scores generated by the system and highlights the suitability of fuzzy logic for handling subjective user preferences that cannot be adequately represented through rigid deterministic rules.

The functional testing results further demonstrate the practical feasibility of the proposed system. All eight black-box testing scenarios were completed successfully, indicating that the system performs reliably across its primary functionalities, including user authentication, recommendation generation, search operations, filtering, and preference updates. Particularly noteworthy is the system's ability to dynamically update recommendations in response to changes in user preferences. This responsiveness enhances user engagement and supports exploratory information-seeking behavior, allowing users to refine their preferences iteratively and immediately observe changes in recommendation outcomes. Such interactive capabilities are essential for modern recommendation systems that aim to improve user satisfaction and decision-making effectiveness.

Compared with previous fuzzy-based recommendation systems, the present implementation provides several methodological and practical contributions. The use of a Mamdani FIS produces linguistically interpretable outputs that are more easily understood by users and library administrators than numerical recommendation values alone. Furthermore, the incorporation of borrowing frequency as an objective behavioral indicator complements subjective inputs such as book ratings and difficulty preferences, resulting in a more balanced recommendation mechanism. The integration of the fuzzy inference engine within a Laravel-based web platform also demonstrates the applicability of fuzzy logic in real-world library information systems and provides a replicable implementation framework for future researchers and practitioners.

Despite these positive outcomes, several limitations indicate opportunities for further improvement. The rule base and membership functions were developed primarily through expert judgment and were not optimized using empirical user interaction data. Additionally, the recommendation process currently considers only three input variables, potentially limiting its ability to capture the full complexity of user reading preferences. Future studies should incorporate user acceptance evaluations, investigate data-driven optimization techniques such as neuro-fuzzy approaches, and explore additional recommendation factors including academic discipline relevance, author reputation, and publication recency. Such enhancements would improve recommendation accuracy, system scalability, and overall user experience while strengthening the practical value of the proposed recommendation framework.

5. Conclusions

5.1 Conclusion

In this study, a Fuzzy Mamdani based book recommendation system for the IIB Darmajaya Library was successfully designed, implemented, and evaluated. The system integrates a three-input (borrowing frequency, book rating, and difficulty level), 27 rule Mamdani FIS with centroid defuzzification into a full-stack web application built on the Laravel-Maria DB-PHP technology stack. Functional testing confirmed error-free operation across all primary user interaction scenarios, and MATLAB based verification validated the mathematical accuracy of the FIS implementation, with the benchmark case (input: [6, 2, 3]) producing the expected recommendation score of 4.3.

The Fuzzy Mamdani approach proved effective in addressing the core challenge motivating this research: accommodating the linguistic uncertainty and multi-criteria nature of book preference specifications in an academic library context. The system's capacity for real-time, preference-responsive recommendation generation represents a meaningful advance over the static, manual search processes that it is designed to supplement. The documented implementation architecture provides a replicable template for analogous university library systems in Indonesia seeking to integrate intelligent recommendation functionality into their existing digital catalogue infrastructure.

5.2 Research Limitations

The current study has several limitations that temper the generalizability of its conclusions. The evaluation was limited to functional correctness testing, and no user acceptance study was conducted to assess the perceived relevance and utility of recommendations from the perspective of actual library patrons. The rule base was parameterized through expert elicitation rather than data-driven optimization, potentially introducing subjective biases. The system's input space was restricted to three variables, which may not fully capture the range of factors influencing book-selection decisions in multidisciplinary academic environments. Finally, the study was conducted at a single institution, and the generalizability of the FIS parametrization to other Indonesian university library contexts with different collection profiles and user demographics has not been tested.

5.3 Suggestions and Directions for Future Research

The findings of this study suggest several promising directions for future research. First, future studies should conduct comprehensive user acceptance testing involving a representative sample of library users to evaluate recommendation relevance, system usability, and overall user satisfaction. In addition to functional performance, quantitative measures such as precision and recall should be employed to assess recommendation quality more rigorously. Furthermore, the recommendation framework could be enhanced through the development of a hybrid architecture that combines the Mamdani Fuzzy Inference System with collaborative filtering techniques. Such an approach would enable the system to incorporate both knowledge-based user preferences and behavioral patterns derived from the borrowing histories of similar users, potentially improving recommendation accuracy and personalization.

Further improvements may also be achieved by adopting data-driven optimization methods and expanding the recommendation context. The application of adaptive neuro-fuzzy techniques could

automatically optimize membership function parameters using historical borrowing and rating data, thereby reducing dependence on expert-defined rules and increasing system adaptability. In addition, future implementations should incorporate additional input variables such as study program, publication year, author impact indicators, and estimated reading time to better reflect users' academic needs. Integration with the institutional digital library would enable access to real-time borrowing data and support long-term personalization based on individual reading histories rather than session-based preferences alone. Finally, extending the implementation to multiple universities would allow researchers to evaluate the generalizability of the proposed fuzzy recommendation framework and support the development of a broader recommendation model applicable across academic library environments.

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Author Contributions
PG Conceptualization, system design, FIS parametrization, implementation, functional testing, original draft preparation and manuscript revision. HW Supervision, conceptualization, methodology review, critical evaluation of system design and results, and final approval of the submitted manuscript.

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