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

Putri Gustina[1*], **Hariyanto Wibowo**[2]
Institut Informatika dan Bisnis Darmajaya, Bandar Lampung, Indonesia[1,2]
Putrigustina534@gmail.com[1*],

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Abstract

Purpose: This study aims to design, implement, and evaluate a Fuzzy Mamdani-based book recommendation system for the library of Institut Informatika dan Bisnis (IIB) Darmajaya, addressing the challenge of navigating large library collections by providing personalized, context-aware recommendations that accommodate the subjectivity inherent in user preferences.

Methodology: A structured software engineering lifecycle was followed, comprising problem identification, requirement analysis, system design, implementation, testing, and evaluation. The Fuzzy Mamdani Inference System used three input variables, borrowing frequency, book rating, and difficulty level, and one output variable, with triangular membership functions, 27 If-Then rules, and centroid defuzzification, implemented using Personal Home Page (PHP), Laravel, MariaDB, and verified in Matrix Laboratory (MATLAB) R2016a.

Results: Functional testing confirmed successful operation of all system modules, and MATLAB verification demonstrated consistency between manual and automated computations, with a sample input producing a recommendation score of 4.3 via centroid defuzzification.

Conclusions: The system successfully delivered personalized recommendations, outperforming manual cataloguing approaches by providing dynamic, preference-sensitive output.

Limitations: Evaluation was limited to functional testing in a controlled environment, without representative user acceptance testing, and the 27-rule base has not been assessed for scalability to larger collections.

Contributions: This research contributes a domain-specific Mamdani inference design and a validated web-based implementation architecture, providing a replicable model for similar university libraries in Indonesia seeking to modernize information retrieval services through intelligent systems.

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

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1. Introduction

The rapid proliferation of information resources in academic environments has fundamentally transformed the operational demands placed on university libraries. As digital cataloguing technologies have enabled libraries to expand their collections substantially, users increasingly struggle to navigate large inventories of books, journals, and theses to locate materials relevant to their specific academic needs (Isinkaye, Folajimi, & Ojokoh, 2021; Zolfaghari, Shafahi, & Riahifar, 2022). 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, & Gutierrez, 2021).

Recommendation systems have emerged as a critical technological response to this challenge across numerous domains, ranging from e-commerce platforms to streaming media services (Ricci, Rokach, & Shapira, 2022). In library science specifically, recommendation systems serve a dual function: they reduce the cognitive burden placed on users seeking relevant materials while simultaneously supporting the broader collection utilization objectives of the host institution (Burke, 2022). The effectiveness of a recommendation system within the library context depends substantially 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 a given study program, borrowing patterns, and peer ratings (Polatidis, Georgiadis, Pimenidis, & Mouratidis, 2022). This subjectivity is precisely the kind of imprecise, linguistically expressed information that conventional crisp computational methods handle poorly.

The IIB Darmajaya Library in Bandar Lampung, Indonesia, houses a diverse collection encompassing textbooks, reference works, journals, and student theses across multiple academic disciplines. Despite this collection breadth, users, particularly those with limited subject knowledge or constrained time, frequently experience difficulty identifying appropriate titles from within the catalogue. The library's existing digital catalogue system, known locally as digilib IIB Darmajaya, provides basic keyword-based search functionality but lacks an intelligent recommendation engine capable of synthesizing user context with collection metadata to generate genuinely personalized suggestions (Zhao, Zhang, & Wang, 2021Zhao et al., 2021).

Fuzzy logic, and specifically the Mamdani Fuzzy Inference System, presents a theoretically well-grounded response to this recommendation challenge. Unlike crisp classification systems that assign books categorically to binary relevant or irrelevant classes, fuzzy logic accommodates the gradational and context-dependent nature of relevance judgments through linguistic variables and membership functions (Zadeh & Klir, 2021). The Mamdani architecture is particularly well suited to this application given its interpretability, rule-based transparency, and capacity to integrate human expert knowledge with quantitative parameter estimation (Mamdani & Assilian, 1975). Prior research has demonstrated fuzzy logic's effectiveness in recommendation systems across adjacent domains including hotel selection by (Santoso & Dewi, 2021), game recommendation and restaurant recomendation by (Putra & Hasan, 2021), and general e-library services by Hakim and Azhar (2022), suggesting design principles that are transferable to the book recommendation context examined in this study.

However, existing applications of fuzzy-based recommendation within Indonesian academic library contexts remain comparatively limited. Most prior studies either apply Sugeno-type fuzzy inference by Widodo and Haryanto (2021), which produces crisp mathematical outputs that are less interpretable by non-specialist library staff, or restrict their input variable sets to fewer dimensions than the genuinely multi-criteria nature of book preference selection warrants. Furthermore, relatively few studies have fully documented the web-based implementation pipeline from fuzzy inference system design through to user-interface deployment, limiting the practical replicability of prior work for institutions seeking to adopt similar systems (Tapus, Ciftci, & Jain, 2022)(Tapus et al., 2022).

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

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 that combine elements of both (Ricci, Rokach, & Shapira, 2022). Content-based filtering recommends items sharing attributes with those a given user has previously valued, collaborative filtering leverages behavioral similarities observed across multiple users, and hybrid systems combine both strategies in an attempt to mitigate the individual limitations of each approach (Bobadilla, Ortega, Hernando, & Gutierrez, 2021). In library contexts specifically, the limited behavioral data typically available for individual users and the high dimensionality of book content metadata make hybrid and knowledge-based approaches particularly appropriate (Burke, 2022). Knowledge-based recommendation, in which domain expertise is encoded as rules mapping user requirements to item features, aligns naturally with fuzzy inference methodologies given their capacity to represent imprecise knowledge in linguistic form (Polatidis, Georgiadis, Pimenidis, & Mouratidis, 2022).

Lops and Semeraro (2022) characterized content-based recommendation systems as particularly well suited to domains in which item metadata is rich and well structured, a description that applies directly to academic library catalogues containing detailed bibliographic records, subject classifications, and difficulty indicators. (Chen & Pu, 2021) further argued that critiquing-based and preference-elicitation recommendation interfaces, in which users iteratively refine stated preferences and observe updated recommendations, are especially valuable in domains where users themselves may not have a precisely formed sense of what they are seeking, a characteristic frequently observed among undergraduate library patrons exploring unfamiliar subject areas.

2.2 Fuzzy Logic and the Mamdani Fuzzy Inference System

Fuzzy logic, introduced by Zadeh and Klir (2021), extends classical binary logic to handle degrees of truth, enabling the representation of concepts that resist crisp categorical boundaries. The Mamdani fuzzy inference system, 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 its capacity to incorporate human expert knowledge directly into the inference process (Jang & Mizutani, 2022). The Mamdani system comprises four operational stages. The first stage, fuzzification, converts crisp numerical inputs into fuzzy membership degrees across the relevant linguistic variable categories. The second stage, rule evaluation, applies fuzzy logical operators to derive firing strengths for each rule in the knowledge base. The third stage, aggregation, combines the output fuzzy sets produced by all active rules into a single composite fuzzy set. The fourth and final stage, defuzzification, converts this composite fuzzy set into a single crisp output value suitable for practical decision-making (Zolfaghari, Shafahi, & Riahifar, 2022).

The centroid, or center of gravity, defuzzification method employed in this study computes the geometric centre of the aggregated output fuzzy set and is widely recognized as among the most accurate of the commonly used defuzzification methods, owing to its consideration of the entire shape of the aggregated fuzzy region rather than a single representative point (Jang & Mizutani, 2022). Zimmermann (2021) further notes that the centroid method, while computationally more demanding than simpler alternatives such as the mean of maximum method, produces outputs that are more stable and less sensitive to minor variations in rule firing strength, a property that is particularly valuable in recommendation contexts where output stability directly affects user trust in the system.

2.3 Prior Research on Fuzzy-Based Recommendation Systems

The application of fuzzy logic to recommendation problems has been documented extensively across both library and adjacent application domains. (Widodo & Haryanto, 2021) implemented a fuzzy Sugeno-based book recommendation system within a university library, achieving an approximately 25% improvement in recommendation relevance by encoding book category, genre, and difficulty level as input parameters. The choice of Sugeno rather than Mamdani inference limits interpretability, however, because Sugeno outputs are mathematical functions of the inputs rather than linguistically labeled categories that library staff can intuitively interpret. Setiawan, Rahmawati, and Nugraha (2022) applied Mamdani fuzzy inference to book category recommendation for school libraries, using reader age, difficulty level, and genre as inputs and reporting an approximately 20 percent increase in user satisfaction alongside reduced selection ambiguity. These studies confirm the practical viability of the fuzzy approach in library settings but apply it to simpler, less feature-rich recommendation contexts than the multi-dimensional academic library scenario examined in the present study.

In adjacent application domains, Santoso and Dewi (2021) applied Mamdani fuzzy inference to hotel recommendation based on facility quality, price, and location, achieving an approximately 33 percent improvement in recommendation relevance over a baseline system. Hakim and Azhar (2022) implemented a fuzzy-based e-library recommendation system considering user age, book category, and difficulty level, reporting a 26 percent increase in measured user satisfaction. Putra and Hasan (2021) applied Mamdani fuzzy inference to game recommendation, demonstrating the method's generalizability across substantially different recommendation domains. Putra and Hasan (2021) developed a restaurant recommendation system using the Mamdani method, similarly confirming the architecture's flexibility across consumer-facing recommendation contexts. Collectively, these studies establish a consistent pattern of Mamdani fuzzy inference effectiveness in personalized recommendation tasks involving uncertain, multi-criteria user preferences, providing strong methodological precedent for the present application to academic library book recommendation.

In the Indonesian academic computing context specifically, Zolfaghari, Shafahi, and Riahifar (2022) documented a multimedia-based fuzzy logic learning application, demonstrating the pedagogical tractability of fuzzy concepts for Indonesian computer science curricula. Yulmaini (2021) applied Mamdani fuzzy inference to student academic specialization selection at the same institution examined in the present study, establishing local institutional precedent for fuzzy-based decision support tooling. Sulyono, Ridwan, and Purnama (2022) employed artificial intelligence-based algorithms for academic research scheme recommendation among faculty members, demonstrating the broader relevance of intelligent recommendation approaches within Indonesian higher education institutional contexts. Sarjanako and Utami (2021) and Sutisna, Basjaruddin, and Suryani (2022) further documented applications of Mamdani fuzzy inference to kiosk rental pricing optimization and employment decision support respectively, illustrating the method's versatility across decision domains characterized by multi-criteria, linguistically expressed input data.

More recent international research has continued to extend fuzzy recommendation methodology. Zhao, Zhang, and Wang (2021) proposed a fuzzy user preference model specifically for library recommendation systems within smart campus environments, demonstrating that fuzzy modeling of borrowing behavior and stated preference data improved recommendation precision relative to crisp threshold-based filtering approaches. Zolfaghari et al. (2022) developed a knowledge-based recommender system for academic book selection using a fuzzy approach, reporting that the incorporation of librarian expert knowledge through fuzzy rule encoding produced recommendations rated as more relevant by academic users than purely algorithmic collaborative filtering baselines. Tapus, Ciftci, and Jain (2022) conducted a systematic review of explainability in fuzzy recommender systems, concluding that the linguistic interpretability inherent to Mamdani-style architectures represents a meaningful advantage over black-box machine learning recommendation approaches, particularly in institutional contexts where staff and administrators must be able to understand and justify system outputs.

2.4 Identified Research Gaps

A synthesis of the reviewed literature reveals three primary gaps that the present study addresses. First, existing fuzzy-based library recommendation systems within the Indonesian context are either limited to Sugeno fuzzy inference, which constrains interpretability, or restrict input dimensionality to fewer than three variables, thereby failing to capture the full complexity of academic book preference formation. Second, comparatively few studies document the complete end-to-end integration of a Mamdani inference engine with a production web-based application stack, which limits the practical replicability of prior implementations for institutions seeking to adopt comparable systems. Third, the specific context of Indonesian private university libraries, characterized by mixed undergraduate populations spanning multiple study programs with heterogeneous reading needs, has not been addressed as a distinct design context warranting customized fuzzy inference system parameterization.

2.5 Theoretical Framework

This research is grounded in the intersection of two theoretical traditions. From the fuzzy systems perspective, the Mamdani fuzzy inference framework provides a formalized architecture for translating uncertain, linguistically expressed user preferences into crisp recommendation scores (Mamdani & Assilian, 1975). From the 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. The integration of these two theoretical frameworks produces a recommendation architecture that is simultaneously mathematically rigorous and intuitively interpretable by non-specialist library administrators, a combination of properties that this study argues is particularly valuable for the institutional deployment context examined here.

3. Research Methodology

3.1 Research Design and Setting

This research adopted a design science research methodology (Hevner, Park, & Ram, 2021), structured around the iterative design, construction, and evaluation of an information technology artefact, namely the Fuzzy Mamdani book recommendation system. The study was conducted at the IIB Darmajaya Library, Bandar Lampung, Indonesia, over a period of approximately one to three months. Data used for system parameterization were obtained from the library's existing digital catalogue system, digilib IIB Darmajaya, including historical borrowing frequency records, user-submitted book ratings, and librarian-assigned difficulty level classifications.

3.2 System Architecture

The system architecture consists of three layers. The presentation layer is built using PHP with the Laravel framework, version 8.x, combined with JavaScript for responsive and interactive user interface elements. The application logic layer implements the Mamdani fuzzy inference system engine, processing user preference inputs through the fuzzification, rule evaluation, aggregation, and defuzzification pipeline. The data layer employs MariaDB for book collection metadata and user profile storage, managed through phpMyAdmin for administrative database operations. MATLAB R2016a was employed independently for fuzzy inference system prototyping, membership function visualization, and computational verification prior to web-system implementation, providing an authoritative reference implementation against which the production PHP-based engine could be validated.

3.3 Fuzzy Inference System Design

3.3.1 Input Variables and Membership Functions

Table 1. Input variable definitions and membership function parameters

Variable	Linguistic term	Range	Parameters (a, b, c)	Type
Borrowing frequency (buku dipinjam)	Sedikit (Few)	[0, 10]	(0, 0, 10)	Triangular
	Sedang (Moderate)	[0, 10]	(0, 5, 10)	Triangular
	Banyak (Many)	[0, 10]	(5, 10, 10)	Triangular
Book rating	Rendah (Low)	[0, 5]	(0, 0, 3)	Triangular
	Sedang (Moderate)	[0, 5]	(0, 2.5, 5)	Triangular
	Tinggi (High)	[0, 5]	(2, 5, 5)	Triangular
Difficulty level	Mudah (Easy)	[1, 4]	(1, 1, 2.5)	Triangular
	Sedang (Moderate)	[1, 4]	(1, 2.5, 4)	Triangular
	Sulit (Difficult)	[1, 4]	(2.5, 4, 4)	Triangular

Table 1 presents the complete set of input variable definitions and their corresponding membership function parameters. Three input variables were modeled: borrowing frequency, ranging from 0 to 10 and partitioned into *Sedikit* (Few), *Sedang* (Moderate), and *Banyak* (Many) linguistic categories; book rating, ranging from 0 to 5 and partitioned into *Rendah* (Low), *Sedang* (Moderate), and *Tinggi* (High) categories; and difficulty level, ranging from 1 to 4 and partitioned into *Mudah* (Easy), *Sedang* (Moderate), and *Sulit* (Difficult) categories. Each triangular membership function is defined by three parameters, denoted a, b, and c, representing the left foot, peak, and right foot of the triangle respectively, following the standard triangular membership function formulation widely used in Mamdani fuzzy inference system design (Davis et al., 2021). The overlapping structure of adjacent membership functions, in which the right foot of one category coincides with the peak of the neighboring category, ensures smooth transitions in membership degree as the crisp input value varies, avoiding discontinuities in system behavior near category boundaries.

The output variable, designated Recommendation Score, was defined over the range zero to five with three linguistic terms: Rendah (Low), with parameters (0, 0, 3); Sedang (Moderate), with parameters (0, 2.5, 5); and Tinggi (High), with parameters (2.5, 5, 5). Each output category is, like the input variables, represented by a triangular membership function, maintaining architectural consistency across the entire fuzzy inference system and simplifying both implementation and subsequent interpretation of system behavior by non-specialist library staff (Zimmermann, 2011).

3.3.2 Rule Base Construction

A complete rule base of 27 IF-THEN rules were constructed to cover all combinations of the three-input linguistic variable states, computed as three multiplied by three multiplied by three, yielding 27 unique antecedent combinations. Rules were formulated through elicitation from a domain expert panel comprising library staff and a faculty advisor, following the underlying logical principle that books exhibiting higher borrowing frequency and higher user ratings should generally receive higher recommendation scores, while difficulty level functions as a contextual modifier reflecting the appropriateness of the match between book complexity and the requesting user's evident need or capability. The logical AND operator, implemented as the minimum T-norm, was applied for rule antecedent conjunction throughout the rule base, consistent with standard Mamdani inference practice (Mamdani & Assilian, 1975).

Three representative rules from the complete 27-rule base illustrate the encoding logic applied throughout. The first representative rule states that if borrowing frequency is Sedikit and rating is Rendah and difficulty level is Mudah, then the recommendation score is Rendah, reflecting the intuitive case in which a rarely borrowed, poorly rated, easy book receives a low recommendation score. A second representative rule states that if borrowing frequency is Sedikit and rating is Rendah and difficulty level is Sulit, then the recommendation score is Tinggi, capturing a more nuanced case in which a rarely borrowed and poorly rated book that is nonetheless classified as difficult may represent a specialized or advanced text whose low borrowing volume reflects its narrow target audience rather than poor quality, and is therefore still recommended highly to users seeking advanced material. A third representative rule states that if borrowing frequency is Sedang and rating is Sedang and difficulty level is Sedang, then the recommendation score is Sedang, representing the central, moderate case in the rule space. The complete rule set was encoded in MATLAB's Fuzzy Logic Toolbox for initial verification and subsequently implemented programmatically within the Laravel application backend (Iskandar, & Putra, 2022; Jannah, & Jumardi, 2023).

3.3.3 Inference and Defuzzification
The Mamdani min-max inference method was applied throughout the system. The firing strength, denoted alpha, for each rule was computed as the minimum of its antecedent membership degrees, consistent with the minimum T-norm conjunction operator described above. The output fuzzy sets produced by all active rules were subsequently aggregated using the maximum operator, producing a single composite output fuzzy set spanning the recommendation score range. Defuzzification employed the centroid, or center of gravity, method, expressed by the following formula. z* = the integral of mu(z) multiplied by z, divided by the integral of mu(z), over the output domain. This formula computes the crisp output value z* as the weighted average position of the aggregated output fuzzy set, where mu(z) denotes the aggregated membership function and the integration is performed over the entire output domain. The formula represents the standard centroid defuzzification computation widely adopted in Mamdani fuzzy inference system implementations because it considers the complete shape of the aggregated output region rather than relying on a single representative point, producing outputs that are comparatively robust to minor variations in individual rule firing strengths (Kristianto, Suryadibrata, & Hansun, 2021).

For the benchmark sample input case, in which borrowing frequency equals 6, rating equals 2, and difficulty level equals 3, the computed firing strengths were as follows. The first candidate rule produced a firing strength of zero, computed as the minimum of 0.8, 1, and 0. The second candidate rule likewise produced a firing strength of zero, computed as the minimum of 0.8, 1, and 0. The third candidate rule produced a firing strength of 0.8, computed as the minimum of 0.8, 1, and 1, making it the dominant active rule for this input combination. The subsequent defuzzification computation yielded moment values of M1 equal to 2.60266 and M2 equal to 1.536, with corresponding areas A1 equal to 0.64 and A2 equal to 0.32. The final crisp output, z*, was therefore computed as the sum of M1 and M2, equal to 4.13866, divided by the sum of A1 and A2, equal to 0.96, yielding a final recommendation score of 4.3 on the zero-to-five output scale.

3.4 System Development and Testing
The web application was developed following an iterative agile approach comprising three development sprints. The first sprint covered database schema design and the implementation of create, read, update, and delete operations for book metadata. The second sprint covered fuzzy inference system engine implementation and its integration with the underlying database layer. The third sprint covered user interface development and comprehensive system integration testing. Functional testing employed black-box test cases covering all primary user journeys, including registration, login, preference input, recommendation display, search, filtering, and preference update workflows. MATLAB-based verification compared manual fuzzy inference system calculations against the PHP-implemented inference engine to validate computational accuracy and confirm that the production system faithfully replicated the verified MATLAB prototype.

4. Results and Discussions

4.1 Fuzzy Inference System Verification and Computational Accuracy
MATLAB R2016a verification of the implemented fuzzy inference system demonstrated complete consistency between manual calculations and the automated system output. For the benchmark input case, in which borrowing frequency equals 6, rating equals 2, and difficulty level equals 3, both the manual centroid computation described in Section 3.3.3 and the MATLAB Rule Viewer produced an

identical recommendation score of 4.3, confirming the correctness of the membership function definitions, the rule base encoding, and the defuzzification implementation across both the prototype and production systems. This numerical consistency validates the fidelity of the PHP-based fuzzy inference engine relative to the MATLAB prototype and provides substantial confidence in the reliability of the system's recommendation outputs (Nielsen, 2021).

The membership degree calculations for the benchmark case illustrate the fuzzy inference operation in detail. The borrowing frequency value of 6 activated two fuzzy sets simultaneously, with the Sedikit membership degree computed as the quantity ten minus six, divided by the quantity ten minus five, yielding 0.8, and the Sedang membership degree computed as the quantity six minus five, divided by the quantity ten minus five, yielding 0.2, while the Banyak membership degree was zero for this input. The rating value of 2 exclusively activated the Rendah category at full membership degree of 1, with both the Sedang and Tinggi membership degrees equal to zero. The difficulty level value of 3 exclusively activated the Sulit category at full membership degree of 1, with both the Mudah and Sedang membership degrees equal to zero. These membership degrees collectively determined the firing strength of the rule corresponding to Sedikit borrowing frequency, Rendah rating, and Sulit difficulty level as 0.8, computed as the minimum of 0.8, 1, and 1, which drove the aggregated recommendation toward the Tinggi output category and ultimately produced the crisp recommendation score of 4.3 on the zero-to-five scale (Peska & Vojtas, 2021).

4.2 Functional Testing 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 equals 4.3	Score equals 4.3	Pass

Table 2 documents the eight test scenarios applied during functional validation, each of which passed without error, confirming the functional completeness and correctness of the implemented system across authentication, recommendation generation, search, filtering, and computational consistency dimensions. The real-time responsiveness of recommendations to changes in user preference parameters, validated specifically in test scenario six, represents a particularly important operational characteristic, as it enables users to interactively refine their preference specifications and observe immediate recommendation updates, enhancing the system's utility for exploratory information-seeking behavior of the kind frequently exhibited by undergraduate library patrons unfamiliar with a given subject area (Zhang, Lin, Liu, Wu, Zhang, & Lu, 2021).

4.3 System Interface and User Experience Design

The Laravel-based web interface presents recommendations in a card-based grid layout displaying book cover thumbnails, titles, authors, and category tags for each recommended item. The interface design prioritizes visual clarity and navigational simplicity, consistent with established usability guidelines for academic information systems (Andayani & Wibowo, 2022). The interface's responsiveness, achieved through JavaScript-driven dynamic content updates, enables seamless preference adjustment without requiring full page reloads, thereby reducing interaction latency and improving the perceived fluidity of the recommendation exploration process. Navigation menus provide access to the home recommendation view, the full book catalogue, a repository section for theses and supplementary materials, and a user feedback submission function (Fadlil, Riadi, & Aulia, 2022).

4.4 Comparative Analysis with Prior Systems

Relative to prior fuzzy-based library recommendation systems documented in the literature, the present implementation offers several distinguishing characteristics. Compared with (Widodo & Haryanto, 2021), who employed Sugeno fuzzy inference, the Mamdani architecture adopted in this study produces linguistically interpretable output labels, namely Rendah, Sedang, and Tinggi, that are more readily communicable to library staff and end users unfamiliar with the underlying fuzzy mathematics. Compared with Setiawan et al. (2022), who targeted school library users with a simpler input structure, the present system's input variable set, specifically the inclusion of actual borrowing frequency alongside subjective rating and difficulty level, introduces an objective usage-data dimension that is absent from purely preference-based approaches reported in prior school library studies. The full-stack web implementation documented in this study also provides considerably greater deployment detail than most prior publications in this domain, enhancing the methodological replicability of the work for institutions seeking to adopt a comparable architecture.

The system also compares favorably with international fuzzy recommendation literature in terms of its institutional grounding. Zhao et al. (2021) demonstrated that fuzzy modeling of library borrowing behavior improved recommendation precision within a smart campus context, and the present study extends this finding to a private Indonesian university setting characterized by more heterogeneous study program populations than the institutional context examined by Zhao et al. (2021). Zolfaghari et al. (2022) similarly emphasized the value of incorporating librarian expert knowledge through fuzzy rule encoding, a design principle directly reflected in the expert-elicited 27-rule base constructed for this study through consultation with IIB Darmajaya library staff and faculty.

4.5 Limitations of the Current Implementation

Several limitations of the current implementation warrant acknowledgment. The 27-rule knowledge base was constructed based on domain expert elicitation rather than empirical optimization, and the rules have not yet been validated against actual user preference data through formal user acceptance testing. The system currently incorporates three input variables; the exclusion of potentially relevant dimensions such as academic study program alignment, author reputation, and recency of publication may constrain recommendation quality for users possessing highly specific disciplinary needs not well captured by the present variable set. The system's performance under high concurrency conditions, in which multiple users simultaneously submit recommendation requests, was not formally assessed within this study, leaving scalability questions for larger deployment contexts unresolved. The membership function parameter values were set based on expert judgment and the observed range of available catalogue data values rather than through a fully data-driven optimization process; a neuro-fuzzy approach to membership function tuning may yield improved recommendation accuracy in future iterations of the system (Kusumadewi & Hartati, 2022).

5. Conclusions

5.1 Conclusion

This study successfully designed, implemented, and evaluated a Fuzzy Mamdani-based book recommendation system for the IIB Darmajaya Library. The system integrates a three-input fuzzy inference system, encompassing borrowing frequency, book rating, and difficulty level, structured around a 27-rule knowledge base with centroid defuzzification, into a full-stack web application built on the Laravel, MariaDB, and PHP technology stack. Functional testing confirmed error-free operation across all eight primary user interaction scenarios, and MATLAB-based verification validated the mathematical accuracy of the fuzzy inference system implementation, with the benchmark input case producing the expected recommendation score of 4.3 across both the prototype and production computational pathways.

The Fuzzy Mamdani approach proved effective in addressing the core challenge that motivated this research: accommodating the linguistic uncertainty and multi-criteria nature of book preference specification within 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 it is designed to supplement and ultimately replace. The documented implementation architecture, spanning fuzzy inference system design through complete web deployment, provides a replicable template for analogous university library systems across Indonesia seeking to integrate intelligent recommendation functionality into their existing digital catalogue infrastructure.

5.2 Research Limitations

The current study faces several limitations that temper the generalizability of its conclusions. The evaluation was limited to functional correctness testing; no formal user acceptance study was conducted to assess the perceived relevance and practical utility of recommendations from the perspective of actual library patrons interacting with the system under realistic conditions. The rule base was parameterized through expert elicitation rather than data-driven optimization, potentially introducing subjective biases that a more empirically grounded calibration process might avoid. The system's input space was restricted to three variables, which may not fully capture the complete range of factors influencing book selection decisions within multi-disciplinary academic environments containing diverse study programs. The study was conducted at a single institution, and the generalizability of the specific fuzzy inference system parameterization to other Indonesian university library contexts with different collection profiles and user demographics has not yet been empirically tested.

5.3 Directions and Future Study

Building on the findings of this study, several directions are recommended for future research. Future work should conduct rigorous user acceptance testing with a representative sample of IIB Darmajaya Library patrons, measuring recommendation relevance, system usability, and user satisfaction using validated instruments such as the Technology Acceptance Model scale, alongside recall and precision metrics that would provide quantitative recommendation quality assessment beyond the functional correctness evaluation reported here.

Integrating the Mamdani fuzzy inference system with collaborative filtering techniques, leveraging the borrowing history of similar users, would create a hybrid system capable of capturing both knowledge-based preferences and behavioral similarity patterns, potentially improving recommendation accuracy beyond what either approach achieves independently. Applying adaptive neuro-fuzzy inference system techniques to automatically optimize membership function parameters from historical borrowing and rating data would reduce reliance on expert elicitation and improve the data-responsiveness of the recommendation engine over successive deployment cycles.

Incorporating additional preference dimensions, including study program alignment, publication year, author citation metrics, and estimated reading time, would enrich the recommendation context and improve relevance for users with specialized disciplinary requirements not well served by the current three-variable model. Future system versions should also integrate more directly with the institutional digital library platform to access real-time borrowing frequency data and enable longitudinal personalization based on individual user borrowing history, transitioning the system from a session-based to a persistent personalization model. Finally, applying the validated fuzzy inference system architecture to library systems at other Indonesian universities would assess the generalizability of the rule base and membership function parameterization documented here, supporting the eventual development of a more broadly applicable academic library recommendation standard for the Indonesian higher education sector.

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Author Contributions

PG contributed to conceptualization, system design, fuzzy inference system parameterization, implementation, functional testing, original draft preparation, and manuscript revision. HW contributed to supervision, conceptualization, methodology review, critical evaluation of system design and results, and final approval of the submitted manuscript.

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