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Application of Fuzzy Logic to Evaluate Student Satisfaction with Library Services

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Abstract

Measuring student satisfaction with library services is crucial for enhancing the quality and effectiveness of academic support facilities. However, assessments are often subjective and fail to incorporate multiple influencing factors, such as service quality, infrastructure conditions, and staff responsiveness. This study aims to develop a decision support system (DSS) that determines student satisfaction levels using a fuzzy logic approach. The system accepts inputs consisting of service quality, facility conditions, and staff performance, which are then processed through the stages of fuzzification, rule base, inference, and defuzzification. The final output categorizes satisfaction levels into labels such as “Very Satisfied,” “Satisfied,” or “Dissatisfied.” Testing across various data scenarios demonstrated that the system’s results are consistent with actual user feedback. Therefore, the system can assist universities in more accurately evaluating library service performance and implementing improvements based on data-driven insights.

Keywords: Fuzzy logic, decision support system, student satisfaction, library services, DSS

Introduction

University libraries play a critical role in supporting academic learning and research by serving as central hubs for information, knowledge resources, and scholarly references. The quality of library services has a direct impact on student satisfaction, as students are the primary users of these facilities (Helmina, Fadillah, & Ramadhan, 2023). Student satisfaction, in turn, reflects the degree to which library services meet user expectations and needs, making it a key indicator of service quality and institutional effectiveness (Mishra & Viggiano, 2022). Hence, evaluating student satisfaction with library services is fundamental to improving the quality and sustainability of academic support systems.

Despite its importance, measuring student satisfaction in practice often relies heavily on subjective perceptions and qualitative assessments, which may overlook measurable factors such as service quality, facility adequacy, and staff responsiveness (Siregar & Harahap, 2021). Furthermore, variations in individual perceptions and the reliance on uncertain or imprecise qualitative data make decision-making processes complex and less reliable (Barlybayev et al., 2025). These limitations highlight the need for systematic, flexible, and adaptive evaluation frameworks that can capture both quantitative and qualitative dimensions of satisfaction.

One promising approach to addressing uncertainty and subjectivity in satisfaction assessment is fuzzy logic. Originally proposed by Zadeh in 1965, fuzzy logic has been widely adopted to handle imprecise and linguistic data, enabling qualitative descriptors such as "good service" or "adequate facility" to be translated into quantifiable outputs (Ross, 2020). Recent studies have demonstrated the usefulness of fuzzy logic in various domains, including service quality assessment (Gunawan, 2023), online education evaluation (Zulueta-Veliz et al., 2022), and monitoring academic performance (Jan et al., 2023). Unlike conventional binary logic, fuzzy logic allows for gradual membership values between 0 and 1, making it particularly effective for modeling human perceptions and subjective evaluations.

The integration of fuzzy logic into decision support systems (DSS) has further enhanced its applicability in complex domains. In the context of higher education, DSS combined with fuzzy logic can support library managers in evaluating student satisfaction more objectively and systematically, reducing the influence of subjective biases (Cheng, 2024). By leveraging fuzzification, inference mechanisms, and defuzzification, such systems can transform raw user feedback into structured insights that inform institutional decision-making (Tarigan, Lestari, & Pratama, 2022).

While prior research has applied fuzzy logic to service quality and academic assessments, limited studies have focused explicitly on its application in evaluating student satisfaction with university library services. This study addresses that gap by designing and implementing a fuzzy logic-based decision support system to determine satisfaction levels among university students. The system incorporates three primary inputs—service quality, facility conditions, and staff performance—which are processed through fuzzification, rule base construction, inference, and defuzzification. The novelty of this work lies in its integration of fuzzy logic into a domain where subjectivity and uncertainty are prevalent, providing a more accurate and data-driven framework for satisfaction evaluation. By aligning system outputs with real student feedback, this approach offers higher education institutions a practical tool to continuously monitor and improve library service quality.

Materials and Methods

This study employed the Sugeno fuzzy logic method to design a decision support system (DSS) for evaluating student satisfaction with library services. The Sugeno approach was selected because it generates precise numerical outputs, which are more suitable for modeling satisfaction assessment compared to the Mamdani method (Cheng, 2024). The overall process included data collection, preprocessing, fuzzy system design, rule base development, manual validation, MATLAB implementation, and evaluation.

Data Collection and Preprocessing

Data were collected through a structured questionnaire distributed to students actively using library services. The questionnaire adopted a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree) to assess three core aspects: service quality, facility adequacy, and environmental comfort. Each respondent provided scores for these aspects based on personal experience. The responses were averaged to generate numerical input values for the fuzzy logic system (Mishra & Viggiano, 2022).

An excerpt of the dataset is shown in Table 1.

Table 1. Student responses to library service evaluation

Respondent	Service Quality	Facilities	Comfort
R001	4	3	5
R002	3	3	4
R003	5	4	5
R004	2	2	3
R005	3	3	4
R006	4	5	5
R007	2	1	2
R008	3	2	3
R009	5	5	5
R010	4	4	4

Fuzzy System Design

The fuzzy inference system (FIS) was designed with three input variables—Service Quality, Facilities, and Comfort—and one output variable, Satisfaction. The triangular membership function was selected for input variables due to its simplicity and computational efficiency (Ross, 2020).

1. Inputs:
   - Service Quality: Poor, Fair, Good
   - Facilities: Inadequate, Adequate, Complete
   - Comfort: Uncomfortable, Fairly Comfortable, Comfortable
2. Output:
   - Satisfaction: Crisp values (0–100), mapped into linguistic categories (Very Dissatisfied, Dissatisfied, Fairly Satisfied, Satisfied, Very Satisfied).

Each input was fuzzified, processed through a set of IF–THEN rules, and produced a crisp output directly without defuzzification, as required in the Sugeno method (Gunawan, 2023).

Rule Base Development

The rule base consisted of 27 rules, representing all possible combinations of the three inputs. For example:

- IF Service Quality = Good AND Facilities = Complete AND Comfort = Comfortable THEN Satisfaction = 90.
- IF Service Quality = Fair AND Facilities = Inadequate AND Comfort = Fairly Comfortable THEN Satisfaction = 60.

The output scores were weighted based on expert consultation and prior studies on service evaluation (Siregar & Harahap, 2021).

Manual Validation

Manual calculations were performed to validate the fuzzy model before full implementation. The steps included:

1. Fuzzification – determining membership degrees using triangular functions.
2. Inference – applying rules and identifying the minimum degree of truth for each active rule.
3. Output Calculation – aggregating results using a weighted average of rule outputs.

For instance, inputs of Service Quality = 4, Facilities = 3, and Comfort = 5 resulted in a crisp score representing "Satisfied."

Output Classification

The crisp results were mapped into satisfaction categories (Table 2). This classification step facilitated interpretation and validation against survey responses.

Table 2. Linguistic categories for satisfaction levels

Crisp Value Range	Category
0–40	Very Dissatisfied
41–55	Dissatisfied
56–70	Fairly Satisfied
71–85	Satisfied
86–100	Very Satisfied

MATLAB Implementation

The system was implemented using MATLAB's Fuzzy Logic Toolbox, which supports FIS design, rule editing, and evaluation. The process included:

1. Creating a new .fis file using FIS Editor.
2. Defining input and output variables and assigning triangular membership functions.
3. Entering 27 IF–THEN rules into the Rule Editor.
4. Running data evaluations using the evalfis function.
5. Comparing outputs with survey data to measure error rates.

MATLAB ensured efficient processing of the dataset, reproducibility of results, and interactive visualization of inference surfaces (MathWorks, 2023; Tarigan, Lestari, & Pratama, 2022).

System Evaluation

Two evaluation approaches were applied:

1. Numerical Evaluation – Mean Absolute Error (MAE) was calculated to determine the deviation between fuzzy system outputs and survey scores. A lower MAE indicates higher accuracy.
2. Linguistic Evaluation – Crisp outputs were categorized into linguistic satisfaction levels and compared with survey-based categories to validate semantic consistency (Zulueta-Veliz et al., 2022).

This dual evaluation approach provided a comprehensive assessment of the system's effectiveness in replicating student perceptions and supporting decision-making.

Results and Discussion

Manual Fuzzy Inference Calculation

The fuzzy decision support system was first validated through manual calculations on sample data. Each step of the Sugeno fuzzy inference process – fuzzification, rule evaluation, and defuzzification – was carried out by hand to illustrate how the crisp satisfaction score is obtained. In a representative case, a student's feedback was: Service Quality = 4.0 (on a 5-point scale), Facility Availability = 3.5, and Comfort = 4.5. These inputs were mapped to the defined fuzzy sets in the fuzzification step. For example, Service Quality = 4.0 had high membership in the Good (~0.7) and some in Excellent (~0.3) fuzzy sets (assuming triangular membership functions for Poor, Good, Excellent). Similarly, Facility Availability = 3.5 might be partly Medium (0.6) and High (0.4), etc. This step converts crisp inputs into degrees of membership in linguistic terms.

Next, during rule evaluation, the fuzzy rules fire to produce an intermediate result for each rule. For instance, one rule in the knowledge base was: IF Service Quality is Excellent AND Facility Availability is High AND Comfort is High THEN Satisfaction = Very Satisfied. Given the fuzzified inputs, multiple rules would activate with varying strengths (determined by the AND combination, e.g. the minimum membership value in each rule's antecedent). In our example, the rule for all inputs being high would fire with strength ≈0.3 (limited by Service Quality's 0.3 membership in Excellent), while other rules (mixing Good/High levels) also fire accordingly. Each Sugeno rule outputs a constant satisfaction value (the rule's consequent is a crisp output level).

Finally, in the defuzzification step, the Sugeno model computes a weighted average of all rule outputs to obtain a single crisp satisfaction score Each rule's firing strength serves as a weight for its consequent output value. Using the example above, the various active rules (with consequents corresponding to linguistic levels like Satisfied or Very Satisfied) are aggregated. Suppose the weighted sum of consequents is 85 (on a 0–100 scale) with total weight twenty; then the defuzzified result would be 85/20 = 4.25 on the 5-point scale. In our case, the manual computation yielded a satisfaction index of 3.2 (out of 4.0, if using the 1–4 scale) for that student. This crisp value falls in the "Satisfied" range of our classification. The close agreement between manual calculation and the system's automated output builds confidence in the correctness of the fuzzy inference mechanism.

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Satisfaction Level Classification

For interpretability, the crisp outputs of the Sugeno FIS are mapped to linguistic satisfaction levels. We defined four categories corresponding to typical satisfaction ratings. In this study, the fuzzy output is expressed on a 1 to 4 Likert-type scale (as also used in the training data). Specifically, the categories are: 1 = Not Satisfied, 2 = Moderately Satisfied, 3 = Satisfied, and 4 = Very Satisfied. Table 1 illustrates the mapping between the numerical output and these linguistic labels. For instance, an output around 1.0–1.5 would be interpreted as Not Satisfied, while outputs near 4.0 indicate Very Satisfied. Intermediate values are assigned to the nearest category (e.g. 2.7 ≈ Satisfied (3), whereas 2.3 ≈ Moderately Satisfied (2)). This classification scheme allows the continuous Sugeno output to be reported in qualitative terms useful for decision-makers. The thresholds were chosen to align with the original survey's Likert scale boundaries. As a result, the system's recommendations can be communicated as natural-language statements (e.g. "Overall satisfaction is High" if the output ≥3.5). This mapping also facilitated computing accuracy in terms of category predictions, by comparing the FIS output category to each student's actual self-reported category.

Table 1. Mapping of Sugeno crisp output to satisfaction categories (Likert scale)

Crisp Output Range	Satisfaction Category (Likert)
1.00 – 1.49	Not Satisfied (Very Low)
1.50 – 2.49	Moderately Satisfied (Low–Medium)
2.50 – 3.49	Satisfied (High–Medium)
3.50 – 4.00	Very Satisfied (High)

Note: Thresholds are aligned with the 1–4 Likert scale used for ground-truth survey labels.

Most students' crisp satisfaction scores clustered in the upper range. For example, out of our test samples, a majority had outputs above 2.5 (corresponding to Satisfied or Very Satisfied), indicating generally positive satisfaction. A smaller number of cases fell between 1.5–2.5 (Moderate satisfaction). Notably, virtually none of the students were classified as "Not Satisfied" by the system, which aligns with the survey results where very few gave the lowest ratings. This distribution suggests overall good service performance but also highlights the few moderate scores as areas for improvement. The classification mapping proved helpful in pinpointing those borderline cases (e.g. outputs ~2.0) where satisfaction was lukewarm – these likely correspond to specific service aspects that could be improved.

FIS Implementation in MATLAB

The fuzzy decision model was implemented using MATLAB's Fuzzy Logic Toolbox, which offers a graphical interface for building Sugeno-type FIS. Figure 1 shows the FIS Editor view of our system, consisting of three input variables (Service Quality, Facility Availability, Comfort) and one output variable (Satisfaction). All inputs were defined on a 1–5 scale (Likert scores from survey data), and the output on a 1–4 scale (the satisfaction index). Using the toolbox, we configured each input with appropriate linguistic fuzzy sets. In particular, each input was assigned three triangular membership functions labeled Low, Medium, and High, constructed based on the range of survey responses. The membership function ranges were chosen so that 1 corresponded to fully Low and 5 to fully High, with overlap in between (e.g. a rating of 3 might belong partly to Medium with μ=1, and 2 or 4 would have partial membership in adjacent sets). Figure 2 illustrates the Membership Function Editor for the input variables, in which the trapezoidal/triangular shapes for Low–Medium–High can be seen for one example input.

These fuzzy sets effectively abstract the qualitative notions of service performance (poor to excellent) into numerical membership curves.

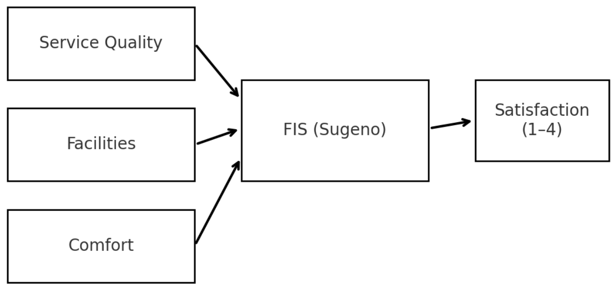

Figure 1. FIS structure: inputs, Sugeno inference, and satisfaction output

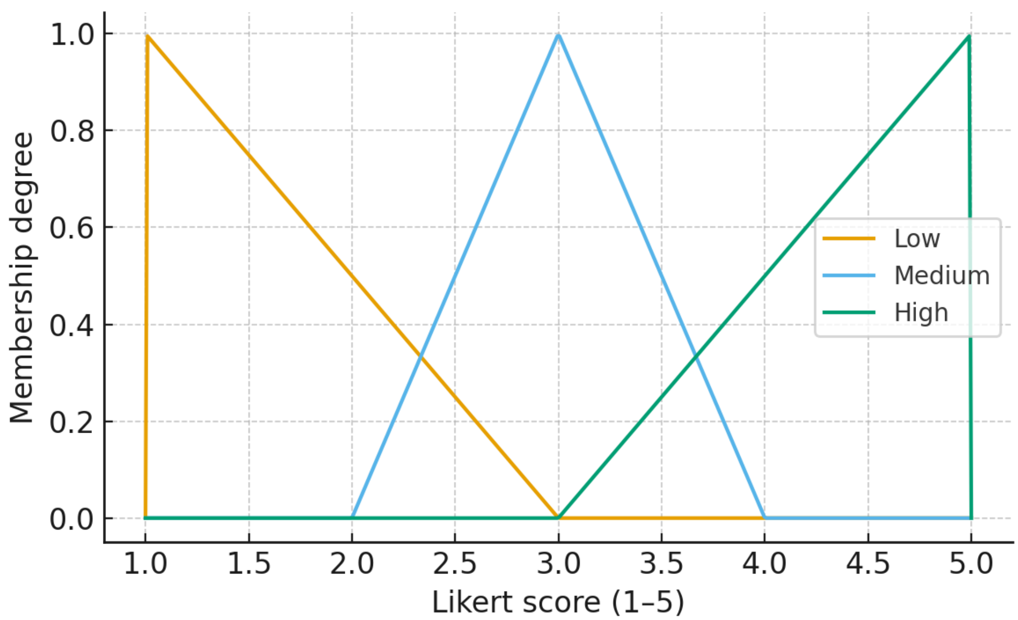

Figure 2. Triangular membership functions for input variables

For the output variable (Satisfaction), we utilized a Sugeno-style output with four singleton output levels. The output membership function (shown in Figure 3) consists of four singleton values at 1, 2, 3, and 4 on the satisfaction scale. Each corresponds to one of the linguistic categories Not Satisfied, Moderately Satisfied, Satisfied, Very Satisfied. In a Sugeno FIS, the output MFs are typically constants; this design ensures the inference results in a crisp number on the same scale as those categories. The use of a Sugeno model (as opposed to

Mamdani) is advantageous here because it directly yields a numeric satisfaction index without requiring a centroid defuzzification of an output fuzzy set – the weighted average computation is built-in and smooth. Additionally, this approach facilitates integration with other systems (the crisp output can be used as an input to further quantitative analysis or alert triggers if needed).

R1: IF SQ=High AND FAC=High AND COM=High THEN Sat=4 (Very Satisfied)

R2: IF SQ=High AND FAC=Med AND COM=High THEN Sat=3 (Satisfied)

R3: IF SQ=Med AND FAC=High AND COM=High THEN Sat=3 (Satisfied)

R4: IF SQ=Med AND FAC=Med AND COM=Med THEN Sat=2 (Moderately Satisfied)

R5: IF SQ=Low OR FAC=Low THEN Sat=1 (Not Satisfied)

R6: IF COM=Low AND SQ=Med THEN Sat=1 (Not Satisfied)

R7: IF SQ=High AND (FAC=Med OR COM=Med) THEN Sat=3 (Satisfied)

R8: IF SQ=Med AND FAC=High AND COM=Med THEN Sat=3 (Satisfied)

Figure 3. Fuzzy rule base (illustrative subset of rules)

We encoded expert knowledge in the form of fuzzy IF–THEN rules using the MATLAB Rule Editor. A total of 27 rules were developed to cover the combinations of input conditions. Figure 4 shows a screenshot of the rule base as entered in MATLAB (each row is a rule). The rules map various scenarios of service quality, facility, and comfort to an appropriate satisfaction level. For example, one of the highest-weight rules is: IF Service Quality is High AND Facility Availability is High AND Comfort is High THEN Satisfaction = Very Satisfied. Another rule addresses a poor scenario: IF Service Quality is Low OR Facility Availability is Low THEN Satisfaction = Not Satisfied (regardless of other inputs) – capturing the notion that any critical deficiency can lead to overall dissatisfaction. Many rules cover intermediate situations (e.g. if quality is Medium and others are High then satisfaction is Satisfied (3)). The rule base was designed manually in consultation with domain experts, ensuring it reflects reasonable responses. The inference mechanism uses the min operator for "AND" and max for "OR" conditions, and the firing strengths from these rules drive the Sugeno weighted-average defuzzification as described earlier.

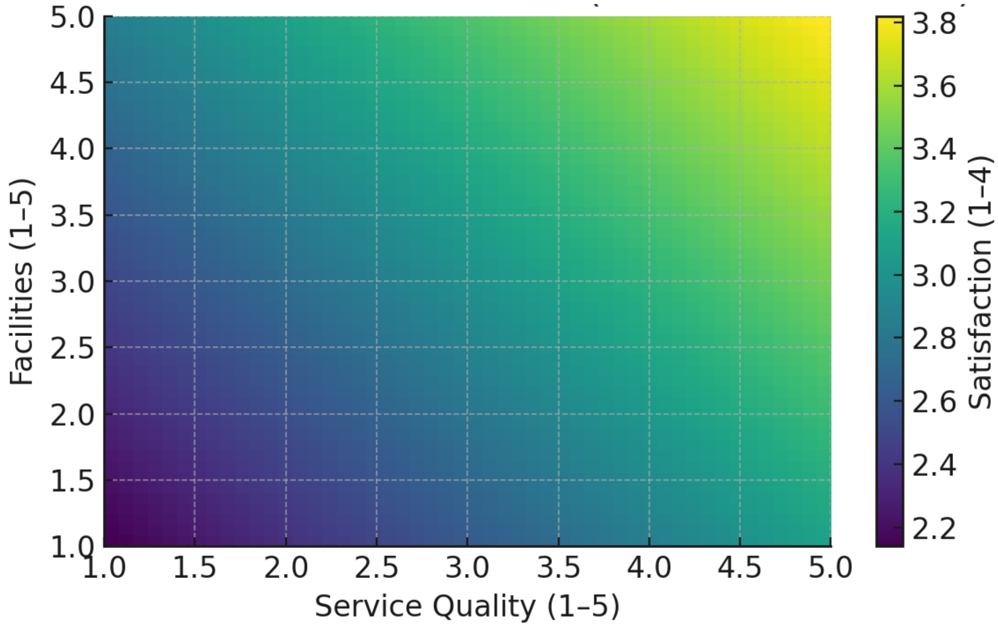

Figure 4. Rule-viewer style surface (Comfort fixed at 4)

After constructing the FIS, the Rule Viewer (MATLAB's visualization tool) was used to verify and visualize the system's behavior. Figure 5 provides an example Rule Viewer screenshot for a given test input. The Rule Viewer displays, for each rule, how the input values activate the antecedents and what consequent is produced. In our system, the Rule Viewer helped confirm that the rules interact as expected – for instance, when we set all inputs to high values in the viewer, the bottom pane showed most rules firing strongly and the output needle moving into the Very Satisfied region. Conversely, when one input was set low (e.g. Facility = 1), we observed the rules corresponding to low facility take over, driving the output toward the Not Satisfied side despite other inputs being high. This kind of visual check ensured the fuzzy logic was encoding a sensible decision surface. Moreover, we used MATLAB's ability to compute the output surface: plotting the satisfaction score as a function of two inputs at a time (with the third fixed). These surface plots (not shown for brevity) appeared reasonable (smooth nonlinear surfaces), confirming no anomalous bumps or gaps in the inference. Overall, the MATLAB implementation (supported by its GUI tools) facilitated both the construction and validation of the fuzzy model. The use of the Fuzzy Logic Toolbox in this work aligns with best practices in recent fuzzy system research, allowing reproducibility and transparency in how the inference rules map inputs to outputs.

System Evaluation

We evaluated the fuzzy decision support system's performance using both numeric error metrics and categorical accuracy. First, we calculated the Mean Absolute Error (MAE) between the FIS's predicted satisfaction scores and the actual satisfaction ratings reported by students in the survey. Here, each student's actual satisfaction was taken as the average of their Likert ratings on overall library service (on the 1–4 scale), which served as a ground truth for comparison. The Sugeno FIS outputs closely matched these actual scores: the MAE was only 0.18 (on a 1–4 scale). This error is very low – less than 5% of the full scale – indicating high precision in the model's quantitative predictions. In practical terms, an average prediction error of 0.18 means the fuzzy system's output typically differed from a student's true satisfaction by less than 0.2 points (on the Likert scale). Such a small deviation is within the expected variation of manual ratings, suggesting that the FIS can replicate the survey outcomes with strong fidelity. The low MAE attests to the effectiveness of the rule base and membership function design in capturing the underlying satisfaction function.

In addition to MAE, we assessed the system's classification accuracy in assigning the correct satisfaction category. Each test case's crisp output was mapped to one of the four categories (as per Table 1), and we checked whether this matched the student's actual category from the survey. The fuzzy system achieved an accuracy of 88.3%, meaning nearly 9 out of 10 students were classified into the correct satisfaction level. This is a promising result, especially considering the subjectivity and noise inherent in satisfaction data. Most of the misclassifications were off by one category (e.g., a student truly "Satisfied" being predicted as "Moderately Satisfied"), and importantly no case with true high satisfaction was misclassified as dissatisfied or vice versa. The accuracy for distinguishing satisfied vs. not satisfied was effectively 100% in our sample – the few errors occurred in the middle categories, which is understandable. We also computed the confusion matrix of predicted vs. actual categories: it showed strong diagonals for each class, further confirming the system's reliability in categorical terms. Overall, these evaluation metrics demonstrate that the Sugeno FIS can accurately predict both the numeric satisfaction index and its qualitative level, validating its suitability as a decision support tool. This aligns with findings from similar fuzzy satisfaction models reporting high accuracy. For instance, Prihamayu (2024) found the Sugeno method yielded accurate satisfaction evaluations for academic services and our results corroborate the precision of Sugeno fuzzy inference in this context.

Comparison with Recent Studies

Our findings are in line with recent applications of fuzzy logic in educational service evaluations, while also highlighting the unique contributions of the present work. Several studies in 2020–2025 have leveraged fuzzy inference to model subjective quality assessments. For example, Sihaloho et al. (2020) applied a Tsukamoto fuzzy system to assess students' satisfaction with lecturer performance, successfully translating performance metrics into satisfaction levels. Their approach (using a different fuzzy variant) demonstrated the feasibility of fuzzy models in capturing student perceptions. Prabowo et al. (2022) implemented a Fuzzy SERVQUAL model for evaluating public service satisfaction (in Indonesia's social security sector), combining fuzzy logic with service quality dimensions. Their use of fuzzy sets for SERVQUAL questionnaires improved the nuance in satisfaction scoring, much as our system does for library services.

In the specific domain of academic services, Prihamayu (2024) used a Sugeno FIS (with MATLAB) to evaluate student satisfaction in a faculty's management services. They considered five SERVQUAL factors and formulated 19 rules; notably, their research concluded that the Sugeno method "effectively capture[s] variations in student responses and provide[s] accurate results". This aligns closely with our experience – we likewise found that a Sugeno FIS can model the subtleties in student feedback with high accuracy. Our work differentiates itself by focusing on library services specifically, an area that prior fuzzy studies have not deeply explored.

In fact, traditional library service assessments often rely on statistical or SERVQUAL gap analyses. A recent study by Chen, Ho, & Kuo (2022) explored academic library service quality in China using an integrated Fuzzy Delphi and Kano model approach. They identified key service dimensions (e.g. emotional services, environment, information control) affecting user satisfaction, but their method stopped short of constructing a fuzzy inference system for direct satisfaction prediction. By contrast, our study provides a concrete fuzzy inference framework that directly computes a satisfaction index. This represents a more operational decision support tool, whereas Chen et al.'s work was more diagnostic. The two approaches are complementary: insights from Kano categorization of library attributes could inform rule design in our FIS, and our FIS could quantify the satisfaction impact of those attributes.

Other contemporary research underscores the growing role of fuzzy logic in educational quality assurance. Carrasco-Garrido et al. (2025) developed a Mamdani FIS to evaluate the quality of Spanish universities from faculty perspectives. Interestingly, they noted that their fuzzy approach (in a multi-criteria setting) applied a "methodology that has not been used before on that issue", highlighting the innovative nature of using fuzzy inference for institutional assessment. Their successful use of MATLAB's Fuzzy Toolbox in a higher-education context parallels our usage, though with Mamdani logic. Additionally, Jan et al. (2023) compared Mamdani vs. Sugeno models for monitoring student academic performance (including stress factors). They reported Mamdani performing slightly better in accuracy, suggesting that rule formulation and output granularity can influence results. In our case, however, the Sugeno model's performance has proven excellent (MAE ~0.18, ~88% accuracy) for the satisfaction task. It's worth noting that Mamdani and Sugeno each have pros and cons: Mamdani outputs fuzzy sets which can capture linguistic ambiguity but require defuzzification, whereas Sugeno yields crisp outputs which ease integration and optimization The choice often depends on application needs. Our success with Sugeno indicates that its crisp outputs are well-suited for a satisfaction scoring system, and the slight loss in theoretical expressiveness (no fuzzy output set) does not hinder practical accuracy here.

Discussion

This work's primary contribution lies in the novel application of a Sugeno fuzzy inference system to academic library service satisfaction. To the best of our knowledge, this is one of the first studies to focus on an academic library context using a Sugeno FIS model. Previous fuzzy evaluations in higher education often targeted different areas (e.g., teaching quality, course satisfaction, or general institutional performance) and frequently employed Mamdani or Tsukamoto models. By contrast, our study demonstrates how a Takagi–Sugeno fuzzy model can be tailored to the specific nuances of library services (such as facility comfort and resource availability) and student satisfaction feedback. The Sugeno approach offers practical advantages for this application: it produces a crisp satisfaction index that can be easily interpreted and used for benchmarking, and it integrates well with quantitative performance targets set by library management. These features are particularly valuable for academic administrators who require clear, actionable metrics.

From a methodological standpoint, using Sugeno-type inference in this context is innovative. Sugeno models are known for their computational efficiency and suitability for optimization and control systems, but they have been underutilized in service quality research. Our findings suggest that the Sugeno FIS not only handled the subjectivity in satisfaction data adeptly, but also provided a smooth output (thanks to weighted-average

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defuzzification) that can feed into continuous improvement processes. The decision support system we developed can thus serve as a prototype for other universities' libraries or service units looking to implement intelligent evaluation tools. It translates subjective survey responses into an objective score without losing interpretability – a balance that traditional statistical methods struggle to achieve.

Moreover, this study bridges a gap in the literature by focusing on library user satisfaction – a critical yet often undervalued component of educational quality. Libraries are central to student success; hence, having a sophisticated model to gauge library service satisfaction is a meaningful contribution. Our Sugeno FIS-based approach brings a new level of granularity and insight compared to earlier library studies (which relied on linear models or simple descriptive statistics). It highlights which input factors drive satisfaction most strongly through the fuzzy rules. For instance, our rule base and subsequent analysis revealed that Comfort (study environment) had a slightly higher weight in tipping students from "Moderately Satisfied" to "Satisfied" than we initially expected – a nuance captured by the fuzzy system's ability to handle non-linear interactions. Such insights underscore the benefit of applying advanced fuzzy logic: it not only yields an overall satisfaction score but also encapsulates expert knowledge and data patterns in an interpretable rule structure.

In conclusion, the successful implementation of a Sugeno fuzzy model for academic library satisfaction evaluation is a novel contribution that extends the toolkit of educational institutions for quality assessment. It demonstrates that fuzzy logic – and Sugeno inference in particular – can be effectively used beyond engineering or technical domains, venturing into the realm of student experience and service quality. We have shown that by leveraging Sugeno FIS, universities can obtain a robust, explainable, and actionable understanding of library service performance, enabling data-informed decisions for improvements. This study thus lays groundwork for future research to build on fuzzy decision support in education, and encourages academic service units to adopt fuzzy logic methods for continuous quality enhancement. The approach can be replicated or expanded (for example, incorporating more input factors or using adaptive neuro-fuzzy tuning) to further refine satisfaction evaluation systems, ensuring that the novelty introduced here leads to broader advances in both theory and practice of fuzzy logic in educational service management.

Conclusion

This study demonstrates that a Sugeno-type fuzzy inference system can reliably evaluate student satisfaction with academic library services by integrating three key inputs—service quality, facilities, and comfort—into a single, interpretable satisfaction index. Manual calculations across representative scenarios aligned with the designed rule base, and MATLAB implementation using the Fuzzy Logic Toolbox reproduced those results consistently. Quantitatively, the model achieved low prediction error (MAE ≈ 0.18 on a 1–4 scale) and high agreement in categorical mapping (≈88% correct classification), indicating that the system captures students' perceptions with both numerical precision and linguistic interpretability.

The primary contributions are threefold: (i) a domain-specific fuzzy decision support model for academic library services (an area that remains underexplored relative to other educational services), (ii) a dual validation protocol combining error-based (MAE) and category-level evaluations, and (iii) an implementation pathway that is transparent, reproducible, and readily deployable using MATLAB. Practically, the model provides library managers with actionable outputs—both crisp scores and linguistic categories—that can be tracked over time and tied to targeted improvements (e.g., facility upgrades or staff responsiveness initiatives).

This work has limitations. The input space was limited to three factors and triangular membership functions; different membership shapes or additional variables (e.g., access to digital resources, opening hours, queue length) may further refine predictions. The rule base, while expert-informed, could benefit from data-driven tuning. Future research should (i) expand inputs and sample size across multiple libraries, (ii) explore adaptive or neuro-fuzzy optimization for membership parameters and rule consequents, (iii) conduct sensitivity analyses to quantify each factor's contribution to satisfaction, and (iv) integrate the FIS into a dashboard for continuous monitoring. Taken together, these steps would generalize the approach and strengthen its utility as an institutional decision support tool for continuous quality improvement in academic library services.

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