

ANALYSIS OF ACADEMIC SATISFACTION LEVEL USING PROBABILISTIC FUZZY INFERENCE SYSTEM

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Article Info:

Received: October 19th, 2025

Accepted: January 7th, 2025

Available Online: January 7th, 2025

Keywords:

*Academic satisfaction; Fuzzy
logic; Probabilistic inference.*

Abstract: Student academic satisfaction is a crucial indicator for evaluating the quality of higher education services. However, the subjective nature and inherent uncertainty in student perceptions render conventional measurement approaches less effective. This study aims to develop and apply a Probabilistic Fuzzy Inference System to analyze the level of academic satisfaction in a more adaptive and logical manner. This method integrates fuzzy logic (to handle linguistic ambiguity) and probability (to address the uncertainty in the contribution of service aspects such as academic administration, academic advisor support, information accessibility, and supporting facilities). Data were collected using a five-level linguistic scale questionnaire, which was converted into fuzzy numbers using triangular membership functions. Inference was carried out using a probabilistic fuzzy rule base. The defuzzification result of the developed system yielded a value of 3.52, which indicates a high level of satisfaction. These findings suggest that the probabilistic fuzzy approach offers a more realistic and flexible evaluation compared to static methods, while being effective in identifying the most influential service aspects. This study contributes to the development of logic-and data-driven academic evaluation models.

1. INTRODUCTION

Student academic satisfaction is an important indicator of the quality of higher education. However, perceptions of satisfaction are subjective and uncertain, making them difficult to accurately analyze using conventional statistical approaches. Previous research has shown the questionnaire based data requires an approach capable of addressing the ambiguity and uncertainty of respondents perceptions [1]. Academic satisfaction evaluation based on conventional methods often fails to capture the linguistic gradation in student responses and ignores the uncertainty of the contribution of various aspects of academic services, such as administration, academic advisors, information availability, and supporting facilities [2]. His necessity encourages the use of methods that can accurately process qualitative (verbal) data into quantitative values, thereby reflecting the respondents natural thought processes.

This problem has been widely discussed in international literature as a major limitation of higher education assessment systems, particularly those relying on deterministic

approaches that are insufficiently adaptive to the diversity, subjectivity and uncertainty inherent in individual student perceptions [1]. To overcome these constraints, this study develops an inference system that integrates fuzzy logic to manage ambiguity in assessments and a probabilistic framework to model the uncertainty and causal influence among various aspects of academic services, in line with fundamental developments in probabilistic fuzzy logic frameworks [3]. This approach is consistent with recent developments in fuzzy and probabilistic theory, which have been increasingly applied to the analysis of survey and questionnaire data in social and educational research to address uncertainty and subjectivity in respondent perceptions [1]. Unlike previous studies that only applied fuzzy or probabilistic methods separately, this combined approach presents innovative value with the ability to dynamically adjust the contribution of each service aspect according to the local characteristics at UIN Sultan Maulana Hasanuddin Banten. This probabilistic fuzzy inference system yields assessments that are more objective, representative, and informative compared to conventional deterministic approaches [4]. Therefore, the combination of the fuzzy method and the probabilistic approach provide a deeper understanding of students' perceptions of academic satisfaction, and serves as a solid foundation for formulating adaptive policies tailored to student needs in the higher education environment [5].

Fuzzy logic is increasingly applied in various fields, yet many academic studies fail to adequately address the stochastic fluctuations inherent in real-time educational services. A key issue in prior research is the reliance on rigid weighting systems that assume the importance of service aspects remains constant, overlooking how student opinions can vary probabilistically across different university operations, as highlighted in reference [6]. Additionally, there is a significant gap in integrating fuzzy sets with probability distributions, particularly in contexts like Islamic state universities, where local cultural values heavily influence student expectations regarding administrative processes and campus facilities, as noted in reference [7]. Without such a hybrid methodology, conventional evaluation tools struggle to adapt to rapidly evolving stakeholder perspectives.

To address these challenges, this study develops an enhanced model for assessing academic satisfaction through a fuzzy probabilistic inference system. The approach combines the strengths of fuzzy sets in managing linguistic vagueness with probabilistic mathematics to handle dynamic weights. This dual-method framework aims to deliver a more accurate representation of service quality at UIN Sultan Maulana Hasanuddin Banten. Ultimately, this model could empower university administrators to pinpoint critical improvement areas aligned with student genuine needs, potentially enhancing the precision of decision-making processes.

2. LITERATURE REVIEW

2.1. Foundational Theory From Fuzzy Logic to Probabilistic Fuzzy Inference Systems

Zadeh made fuzzy logic to fix problems with strict yes or no systems and handle the natural unclear parts of human talk. By letting data go from 0 to 1, fuzzy logic gives a bendy way to measure personal feelings like how students see school services. For example, in school feedback forms, emotions like somewhat happy or mostly sad show up better with fuzzy tools than with just yes or no options.

But real info has more than just unclear words; it also has unexpected parts from survey answers. Fuzzy logic deals with the personal part, but we need chance methods for these random bits. Mixing them makes the Probabilistic Fuzzy System (PFS), which handles both unclear ideas and random changes together. The Probabilistic Fuzzy Inference System

(PFIS) goes further by adding chance weights to fuzzy rules based on how trustworthy they are. The whole process from making inputs fuzzy using rules, putting them together, and changing back uses chance patterns to get better results.

2.2. Evolution of FIS and PFIS in Educational Research

Fuzzy Inference Systems (FIS) are used a lot in education. Imam et al. applied the Fuzzy Mamdani way to check student joy with Course Learning Outcomes (CLO), giving steadier checks than simple methods. Xu et al. combined Fuzzy TOPSIS with a cloud model to look at online learning feedback, skillfully handling different views from people. Carrasco-Garrido et al. [8], [9] used a Mamdani FIS to check university work, pointing out that study help and fast replies were big parts of total happiness [10]. Still, most work uses basic fuzzy ways. Cardiel-Ortega et al. added a PFS for Failure Mode and Effects Analysis (FMEA) like spotting dangers in schools [5]. Their method, while on dangers, showed how adding chances improves accuracy and shows result differences, a thing this study uses for the changing area of student satisfaction.

2.3. Comparative Summary of Existing Literature.

The table here outlines the main studies showing their respective areas and weak spots that this project wants to fix.

Table 1. Comparative summary of existing literature

Author(s)	Year	Method	Domain	Limitations
Imam et al. [8]	2020	Fuzzy Mamdani	Student satisfaction (CLO)	Skips erratic changes in feedback data
Xu et al. [9]	2021	Fuzzy TOPSIS (cloud model)	Online learning satisfaction	Leaves out the role of random doubt
Carrasco-Garrido et al. [10]	2019	Mamdani FIS	University system quality	Gives steady findings without chance factors
Cardiel-Ortega et al. [5]	2022	PFS (for FMEA)	Risk assessment (analogous to education)	Focused on FMEA; not directly applied to academic satisfaction.

This piece stands out by going past the steady style of usual FIS. With Probabilistic Fuzzy Inference System (PFIS), this method deals with the fogginess of views and the instability of service shifts. Unlike research that relies on a single approach, this framework integrates fuzzy logic with probabilistic reasoning to develop a responsive tool tailored to the unique context of Islamic higher education institutions. It draws from wins like Cardiel-Ortega et al. while tailoring them to current school needs [5]. By allowing service components to adjust dynamically, the framework captures subtle changes in student expectations over time. This adaptability supports more grounded interpretations of satisfaction levels across administrative and academic domains. As a result, the model offers practical insights that can guide context-aware strategic prioritization within faith-based higher education institutions.

3. METHODOLOGY

3.1. Approach and Research Design

This research employs a descriptive quantitative approach that aims to analyze the level of student academic satisfaction through the application of a Probabilistic Fuzzy System (PFS). We selected this approach because it effectively models the inherent

uncertainty and ambiguity of respondents perceptions toward academic services when expressed in linguistic terms. The fuzzy-probabilistic method offers an advantage over conventional deterministic models by combining the concepts of fuzzy logic and probability theory to produce more realistic and informative decisions [11].

3.2. Data Source and Type

The empirical foundation of this research rests on primary data gathered through a structured, closed-ended survey administered to active students at the Faculty of Science, the State Islamic University of Sultan Maulana Hasanuddin Banten. To ensure depth in the assessment, the instrument encompasses five key service dimensions, with 18 measurement items, namely: Academic Administrative Services, Availability and Support of Academic Advisors, Study Plan (KRS) and Study Results (KHS) Processes, Access to Academic Information, and Academic Supporting Facilities. Respondents articulated their experiences using a 5-point Likert-style linguistic scale, ranging from Very Dissatisfied (1) to Very Satisfied (5), with Moderately Satisfied (3) as the neutral anchor. This linguistic approach was deliberately chosen for its seamless conversion into fuzzy membership functions, which far more accurately represent the "haziness" of human perception than binary metrics [5].

The questionnaire was deployed digitally through the university's official learning management system (LMS), targeting students who had completed at least two academic semesters to ensure a stable perspective on institutional performance. This purposive sampling ensures that the data directly mirrors the authentic, lived experiences of the stakeholders most impacted by the university's academic service quality.

3.3. Research Variables

The study involves six main variables, consisting of five independent variables and one dependent variable. The **dependent variable** is academic satisfaction level. The **Independent Variables** include:

- Academic Administration Services (**X1**): Covering the speed, friendliness, and courtesy of staff, clarity of academic procedures (e.g., Study Plan Card, Study Results Card, academic leave), timeliness of schedule information, staff's ability to answer questions/provide solutions, ease of access to online services, and appropriateness and consistency of service operating hours.
- Availability and Support of Academic Advisors (**X2**): Measuring the ease of contacting academic advisors and the quality of educational guidance and support provided by the advisors to students.
- Study Plan and Study Results Process (**X3**): Covering the ease and efficiency of the procedure for completing the Study Plan Card every semester, as well as the accuracy of the information listed in the Study Results Card.
- Academic Access and Information (**X4**): Covering the availability, clarity of content, and ease of accessing academic information (schedules, announcements, academic calendar) through various media (web, WhatsApp groups, etc.).
- Academic Supporting Facilities (**X5**): Including the availability of adequate classrooms, access to Wi-Fi for academic activities, library services, and ease of access to educational references.

3.4. Sampling Technique

The sampling method used is purposive sampling, which involves the deliberate selection of respondents based on specific criteria relevant to the research objective [12]. The sample size is 82 active students who have utilized academic services for at least two semesters. This number is considered adequate for exploratory research employing a fuzzy-probabilistic model, as such approaches emphasize the quality of inference and knowledge representation under uncertainty rather than reliance on large sample sizes and classical statistical significance [13].

3.5. Data Collection Method

Data collection involved distributing online and face to face questionnaires. Each question item was formulated in linguistic terms, which would later be converted into fuzzy values. Validity was confirmed via content validity, achieved through discussions with fuzzy methodology and education management specialists, reliability was established using the Cronbach's Alpha coefficient [14].

3.6. Data Analysis Method

The data analysis procedure was conducted through five main steps:

- **Step 1. Fuzzification of Linguistic Data**

Each linguistic answer is converted into a fuzzy value using the triangular membership function [13] as shown in Equation (1):

$$\mu_A(x) = \begin{cases} 0, & x < a \\ \frac{x-a}{b-a}, & a \leq x < b \\ \frac{c-x}{c-b}, & b \leq x < c \\ 0, & x \geq c \end{cases} \quad (1)$$

Where a, b, and c are the lower limit, peak, and upper limit of the triangular function, respectively.

- **Step 2. Formulation of fuzzy rules**

The relationship between variables is represented in the form of **IF THEN** linguistic logic rules, for example, **IF X1 is High AND X2 is Medium THEN Y is Satisfied** [13].

- **Step 3. Probabilistic weighting**

Each rule is assigned a probabilistic weight based on its frequency of occurrence in the empirical data, as shown in Equation (2) [15]:

$$w_i = \frac{f_i}{\sum_{j=1}^n f_j} \quad (2)$$

Where f_i is the frequency of the premise condition of the i-th rule, and n is the total number of fuzzy rules.

- **Step 4. Fuzzy-probabilistic inference process**

The inference process is performed by combining the membership function and the probabilistic weight using the max-product operator, as shown in Equation (3) [11]:

$$\mu_{output}(y) = \max (w_i \cdot \mu_i(x) \cdot \mu_{Bi}(y)) \quad (3)$$

This result represents the strength of the contribution of each rule to the final decision.

- **Step 5. Defuzzification**

The fuzzy value resulting from the inference is then converted into a single numerical value (y) using the centroid method, as shown in Equation (4) [11]:

$$y = \frac{\int y \cdot \mu_{output}(y) dy}{\int \mu_{output}(y) dy} \quad (4)$$

The final value (y) is converted back into a linguistic scale (e.g., "Satisfied" or "Very Satisfied") for easy interpretation.

3.7. Summary of Analysis Procedure

The entire analysis was performed using the Python software to process the membership functions and the probabilistic fuzzy inference system. This approach allows for the visualization of relationships between variables and produces a satisfaction value that is more representative compared to conventional statistical methods [13].

4. RESULTS AND DISCUSSION

The results show that students feedback academic is highly appreciated by students at UIN Sultan Maulana Hasanuddin Banten on average but comments show that there are still many unsatisfied students. Defuzzified score on a average of 3.52 suggests that students generally appreciate the academic services available”, but the comments show that students’ feedback are unsatisfied and there are many students who need more academic services! There is a need to improve the services as the score is average. Table 1 shows that students’ satisfaction in the are of Availabilty and Support of Academic Advisors (X2) is the highest of all. 3.78 is a pretty good high score. 3.72 which is the score of the Management of Study Plans and Study Results (X3) also is a pretty good score.

Table 2. Average Defuzzified Scores of Academic Service Dimensions

Variable	Academic Service Dimension	Mean Score	Category
X1	Academic Administrative Services	3.67	Good
X2	Availability and Support of Academic Advisors	3.78	Good
X3	Study Plan (KRS) and Study Results (KHS) Process	3.72	Good
X4	Access to Academic Information	3.65	Good
X5	Academic Supporting Facilities	3.31	Fair

The respondents are pleased that there are good and effective communications and strong relationships among students and the teaching staff who are involved in the administration of the studied units. X5 Academic Supported Facilities (X5) 3.31 is the lowest score of all which shows that academic surrounding facilities and the physical learning environment are more behind than other areas. However, it is still a big gap, it is still the lowest score. This is clearly shown in the Figure 1.

The primary strength of the fuzzy-probabilistic approach lies in its ability to capture the linguistic nuances and inherent uncertainty in student perceptions. Unlike conventional statistical methods, which are deterministic and linear, this methodology utilizes linguistic representations ("somewhat satisfied," "quite good") converted into fuzzy values, making

the analysis more realistic and adaptive to subjective human judgment. Furthermore, the inclusion of probabilistic weights assigned to each fuzzy rule enhances the reliability of the inference results, as these weights are based on empirical frequencies reflecting the genuine tendencies of the respondents.

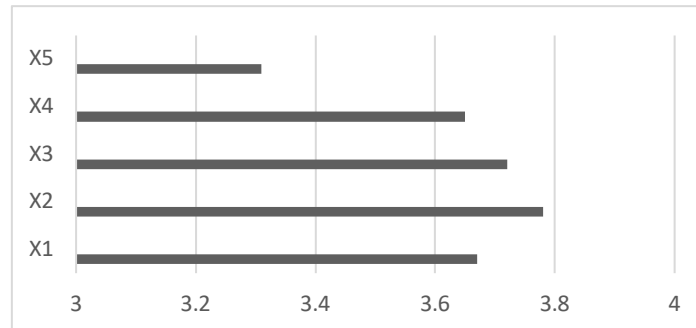


Fig 1. Comparison of Defuzzified Scores Across Academic Service Dimensions

The findings of this study provide several conceptual advancements over the existing literature. For instance, previous research often conceptualized academic satisfaction as a unidimensional nature, encompassing student characteristics, instructional quality, service and engagement factors [2]. MARTIN In line with the conceptual critique of deterministic models that yield rigid outputs and limited uncertainty representation, probabilistic fuzzy systems provide an integrated framework that accommodates both fuzziness and randomness, enabling more flexible, nuanced and informative inference rules than conventional deterministic approaches [11].

This study confirms and extends the findings of Gupta et al. [16], who showed that student mentoring significantly influences student satisfaction and engagement in higher education. This viewpoint is substantiated by Makaremi et al. [17], who asserted the increasing importance of the physical learning environment in the post-pandemic education ecosystem.

This research aimed to analyze the level of student academic satisfaction by employing the probabilistic fuzzy inference system as an evaluation approach capable of representing the uncertainty and ambiguity in student perceptions of educational services. Based on the analysis, the average defuzzification value of 3.52 categorized as "Good" leads to the conclusion that students are generally satisfied with the academic services provided by UIN Sultan Maulana Hasanuddin Banten.

Specifically, the roles of academic advisors and study plane and study results administration were identified as the most influential factors contributing to high satisfaction, underscoring the importance of personal interaction and efficient academic processes. Conversely, academic supporting facilities registered the lowest score, indicating a critical performance gap that the institution must address. Methodologically, the study validates the superiority of the fuzzy-probabilistic approach over conventional deterministic methods, given its capacity to capture both linguistic and probabilistic variations in perception data. His validation confirms that the Fuzzy-Probabilistic model is essential for accurately measuring complex phenomena, such as satisfaction. Moving forward, the institution should leverage these nuanced findings, prioritizing immediate investment in modernizing facilities to align physical resources with the high quality of its advisory and administrative services.

5. CONCLUSION

In general, the level of student academic satisfaction falls into the "Good" category, with an average defuzzified score of 3.52. The average defuzzification score indicates that educational services are operating quite effectively. Specifically:

- a. Key Determinants: The role of academic advisors and the study plane and study results administration process emerged as the most significant drivers of high student satisfaction, underscoring the necessity of robust personal interaction and efficient core procedures.
- b. Weakest Performance Aspect: Academic supporting facilities (physical infrastructure) showed Ineffective performance, indicating a performance gap between optimal human-interaction services and the condition of the physical infrastructure.

The probabilistic fuzzy inference system validated its robustness. Furthermore, it demonstrated greater realism in measuring academic satisfaction, owing to its ability to handle the linguistic ambiguity and uncertainty inherent in student perceptions. Several study limitations influence the above conclusions.

- a. Variable Scope: The research was restricted exclusively to core academic services, thereby omitting non-academic factors (such as psychological or social determinants) that could potentially influence overall satisfaction levels.
- b. Model Complexity: The inference model's continued reliance on simple membership functions may not adequately represent the complexity inherent in the relationships between student perception variables.

Based on these findings and limitations, we recommend that future research proceed as:

- a. Adaptive Model Development: Future efforts should refine fuzzy-probabilistic models by utilizing Gaussian or trapezoidal membership functions to achieve superior conformity with empirical data distributions.
- b. Variable Expansion: Incorporate non-academic determinants (such as learning motivation or psychological support) into the satisfaction model to establish a more comprehensive multifactorial construct.
- c. Real-time Deployment: Test system integration with a digital campus evaluation platform to facilitate the real-time application of results for strategic decision support.

ACKNOWLEDGMENT

The author expresses sincere gratitude to the State Islamic University Sultan Maulana Hasanuddin Banten (UIN SMH Banten), specifically to the Faculty of Science and Technology, for the invaluable support and facilities provided throughout the research process.

Special thanks are also due, extended to all participating student respondents who diligently completed the questionnaires and provided the valuable information that formed the basis for the analysis in this study.

We also appreciate the conceptual, methodological, and technical guidance provided by our colleagues and supervisors during the preparation of this research. The moral and

collaborative support from the academic community played a crucial role in the completion of this study.

The author sincerely hopes that the results of this research will provide a tangible contribution to the development of academic evaluation systems based on computational intelligence within higher education institutions.

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