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An Adaptive Decision Support System for Student Behavior Assessment Using Fuzzy Mamdani Inference

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Abstract: Student behavior assessment in Indonesian secondary schools typically relies on a rigid point system that tracks compliance but ignores peer-observable social behavior, lacking a mechanism to compensate across dimensions. This study presents SiPandu, a Fuzzy Mamdani-based Decision Support System that integrates three variables, attendance percentage (X1), cumulative behavior points (X2), and peer-assessment scores (X3) into a single adaptive score using the ADDIE R&D model. These variables were standardized to a [0,100] scale and processed via 27 IF-THEN rules with discrete centroid defuzzification, yielding four categories: Needs Guidance, Fair, Good, and Excellent. Content-validated by a school counselor, the peer-assessment instrument aligns with Indonesian Ministerial Regulation No. 10 of 2025. The prototype was piloted on 39 students in one class at a public senior high school in Bandung. Functional (black-box) testing confirmed that the system met all specified requirements, including its data-access security controls. System Usability Scale (SUS) testing (n=17) yielded a mean score of 65.88 (OK/Marginal), revealing a gap between administrative users (92.5) and students (62.33). Manual simulation confirmed the model's compensation mechanism, where strengths in one dimension offset weaknesses in another without resorting to binary pass/fail outcomes. These findings show that Fuzzy Mamdani inference effectively softens the rigidity of conventional behavior assessments while remaining interpretable for non-technical homeroom teachers.
Keywords: Fuzzy Mamdani; Decision Support System; Student Behavior Assessment; Peer Assessment; Gamification

1. INTRODUCTION

Assessing student behavior is a mandatory part of character education in Indonesian secondary schools, yet in practice most schools still rely on a cumulative point system that reduces a student's behavioral profile to a single tally of violations. A recent evaluation of point-based discipline enforcement found that such systems register compliance but fail to capture the social and character dimensions that a purely punitive tally cannot reflect, leaving no room for gradation between a student who is occasionally late and one who is consistently disruptive [1]. This rigidity is compounded by the fact that conventional point systems are additive: a strength in one behavioral dimension, such as near-perfect attendance, cannot offset a weakness in another, such as a low peer-observed collaboration score, even though both dimensions plausibly describe the same student's overall character.

Fuzzy logic, introduced by Zadeh [2], offers a reasoning framework that accommodates partial degrees of membership rather than the crisp full-or-none membership of conventional sets, making it well suited to gradations of behavior that resist binary classification. Within Indonesian educational

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research, Mamdani inference has been consistently favored over Sugeno or Tsukamoto whenever the output must remain interpretable to a non-technical decision-maker: applications range from student-personality classification [3] and new-student admission screening [4] to plant-disease diagnosis [5]. What these applications share is the same underlying appeal, fuzzy sets that domain experts can validate directly rather than opaque statistical models, yet none of them evaluates day-to-day behavioral or affective indicators, the gap this study addresses below.

Despite this body of work, three gaps remain unaddressed. First, existing fuzzy applications in education overwhelmingly target academic achievement; even international work that models behavioral indicators, such as a fuzzy propositional model of PISA response-process data [6] or a fuzzy-and-machine-learning system for assessing university students' personality development and career readiness [7], still centers on academic performance prediction or post-graduation employability rather than day-to-day, school-based conduct. Second, peer-assessment studies, such as an implementation of peer assessment to evaluate students' Pancasila learner profile [8], treat peer judgment as a stand-alone grading source rather than as one input aggregated with more objective school-observation data such as attendance and violation records. Third, several fuzzy implementations in education are built on fixed-parameter simulation software rather than production systems whose membership functions and rule base a school can reconfigure without touching the source code.

To close these gaps, this study designs and implements SiPandu, a Fuzzy Mamdani-based Decision Support System (DSS) that integrates attendance percentage (X1) and cumulative behavior points (X2) from school records together with a peer-assessment score (X3) into a single adaptive behavior score, extending fuzzy inference beyond the academic-achievement focus of prior work into everyday behavioral assessment, treating peer judgment as one aggregated input rather than a stand-alone score, and exposing the model's parameters through a production-grade reconfiguration interface rather than fixed-parameter simulation software. Positioning SiPandu as a DSS follows the principle that final decision authority must remain with the human user [9], consistent with modern DSS practice that increasingly incorporates criteria that are subjective or cannot be measured against a rigid threshold [10], the system therefore outputs a recommended score and category rather than an automatically executed sanction, leaving the homeroom teacher as the final decision-maker. The five dimensions of the peer-assessment instrument, Akhlak Mulia (moral conduct), Kewargaan (citizenship), Kolaborasi (collaboration), Kemandirian (independence), and Komunikasi (communication), were mapped to the graduate-competency dimensions of Indonesian Ministerial Regulation No. 10 of 2025 [11] and content-validated by the school counselor, giving the otherwise subjective X3 variable a defensible conceptual grounding.

The Mamdani method was chosen over Sugeno because its output is expressed as interpretable fuzzy sets rather than a linear or constant function, a direct comparison of Mamdani and Sugeno inference confirmed that Mamdani's linguistic, rule-based output is better suited to decision-making that requires interpretable reasoning, whereas Sugeno remains preferable for numeric system modeling and automatic control [12], a trade-off that matches SiPandu's target user, the homeroom teacher, who is expected to interpret rather than recompute the result.

Beyond the inference engine, SiPandu incorporates a gamification layer to sustain student motivation, an approach with robust empirical support: gamification consistently improves learner motivation and engagement in educational settings, particularly through elements such as points, badges, and progress feedback that satisfy learners' psychological need for competence [13], [14]. Because SiPandu's users are adolescents, its badge design further draws on evidence that this age group responds more strongly to visual, concrete recognition than to abstract praise [15].

SiPandu was developed using the ADDIE (Analysis, Design, Development, Implementation, Evaluation) research and development model and piloted on 39 students in one class at a public senior high school in Bandung. This study accordingly aims to (1) design a Fuzzy Mamdani model that integrates objective school-observation data with subjective peer-assessment data into one adaptive behavior score, (2) implement the model as a reconfigurable web-based decision support system, and (3) evaluate the resulting system's functional validity and usability.

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2. RESEARCH METHODOLOGY

This study adopts a Research and Development (R&D) approach using the ADDIE model, mapped explicitly onto model-driven decision support system development activities, domain-knowledge elicitation and instrument validation with the school counselor during Analysis, formulation of the fuzzy sets, membership functions, and rule base during Design, translation of that model into a web application during Development, deployment to real student data during Implementation, and functional and usability testing during Evaluation [9]. The research was conducted at a public senior high school between November 2025 and June 2026.

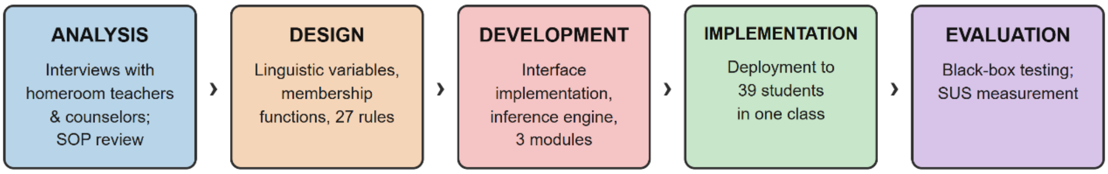

Figure 1. ADDIE research and development stages mapped to model-driven decision support system development activities

2.1 Data Collection and Sampling

Requirements were elicited through a literature review, direct field observation of the school's existing behavior-recording workflow, and semi-structured interviews with the school counselor and a homeroom teacher, who jointly validated the choice of input variables and the linguistic boundaries used in the fuzzy design. Two different samples were used for two different purposes. The implementation sample, the group whose behavior data was processed by the system to produce actual Z* scores, was selected using purposive sampling, one class (39 students) in the first year of senior high school, a level identified by school staff as needing the most intensive character-formation monitoring. A single class was considered sufficient for this pilot because the study's primary objective was to validate the functional feasibility and usability of the fuzzy-based scoring mechanism under real classroom conditions, rather than to establish generalizable behavioral norms across the school population. Accordingly, the resulting Z* score distribution and usability findings should be read as evidence of the system's technical and practical viability, not as a representative behavioral profile of the broader student body. This scope limitation is revisited in the Discussion section.

2.2 Fuzzy Model and System Development

Each of the three input variables and the output variable were standardized to a common universe of discourse of [0,100] and partitioned into three linguistic sets (Low, Medium, High) for the inputs and four categories (Needs Guidance, Fair, Good, Excellent) for the output. Three sets per input variable was chosen as a balance between assessment granularity and expert-validation feasibility, three linguistic sets per variable yield $3^3 = 27$ rules that a single domain expert can review exhaustively in one session, whereas five or seven sets would multiply the rule base to 125 or 343 rules respectively, a scale no longer practical to validate manually. Membership function shapes and boundaries were determined by two overarching criteria: continuity of coverage and grounding in real institutional thresholds. Trapezoidal functions were used for the extreme sets (Low, High) and a triangular function for the middle set (Medium), with adjacent sets deliberately overlapping so that no input value falls into a membership-free "dead zone." The boundary values themselves were anchored to the school's official attendance and disciplinary-escalation thresholds for X1 and X2, and to the school counselor's expert judgment for X3.

The inference engine follows the Mamdani procedure in four stages, fuzzification of the crisp X1, X2, and X3 inputs into membership degrees, evaluation of the 27 IF-THEN rules using the MIN

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operator to obtain each rule's firing strength, MAX-based aggregation of rules sharing the same output category, and discrete centroid defuzzification over 1,000 uniformly spaced sample points on the output universe to obtain the crisp score Z*. This sampling resolution was chosen because it keeps rounding error in the centroid calculation negligible for category assignment while remaining computationally inexpensive to run inside a server-side function on every score request.

The prototype was implemented as a three-tier web application. The presentation layer uses Next.js 16.2 with the App Router, React 19, TypeScript 5, and the shadcn/ui component library styled with Tailwind CSS. The business-logic layer combines Next.js Server Actions for CRUD operations with PostgreSQL triggers and functions for operations that must remain consistent regardless of the access path, such as recalculating the cumulative behavior-point balance (X2) and aggregating peer-assessment submissions into X3. The data layer is provided by Supabase, a PostgreSQL 15-based backend-as-a-service offering authentication and Row Level Security (RLS), which restricts every database query to the rows a given authenticated role is entitled to see, across a 21-table relational schema.

2.3 Evaluation Methods

System functionality was evaluated using black-box testing, an approach that validates a system's outputs against given inputs without inspecting its internal source code [16]. Twenty test scenarios (coded BB-01 to BB-20) were derived from 13 functional requirements and 1 security-related non-functional requirement, and were executed by the researcher on 9 June 2026 against the production deployment using real data from one academic period, with a separate test account for each of the three user roles.

Usability was evaluated using the System Usability Scale (SUS), a ten-item, five-point Likert questionnaire developed by Brooke [17]. Odd-numbered items are worded positively and even-numbered items negatively, each respondent's per-item contribution is computed as (response − 1) for odd items and (5 − response) for even items, summed and multiplied by 2.5 to yield a 0-100 score. To reduce single-source bias, the study combined two independent evaluation channels, functional correctness through black-box testing and perceived usability through SUS, and relied on the school counselor as an independent domain expert to validate the peer-assessment instrument rather than having the researcher self-certify its content. Both evaluation channels nonetheless carry scope limitations, most notably the single-class field trial and the fact that functional testing was conducted by the system's own developer, which are addressed in detail in the Discussion section.

To respond to calls for comparative validation, Mamdani inference was additionally benchmarked against zero-order Fuzzy Sugeno and Fuzzy Tsukamoto inference on the same 39-student dataset, using identical input membership functions and the same 27-rule antecedents. For Sugeno, each rule's consequent was replaced with a singleton equal to the peak or plateau boundary of the corresponding Mamdani output set from Table 1 (Needs Guidance = 40, Fair = 55, Good = 80, Excellent = 95). For Tsukamoto, which requires each consequent to be monotonic, the two shoulder categories (Needs Guidance, Excellent) reused their existing monotonic membership functions directly, while the two triangular categories (Fair, Good) were represented by the rising half of their respective triangles, reusing the breakpoints already published in Table 1 rather than introducing new parameters.

3. RESULT AND DISCUSSIONS

This section presents the outcomes of the ADDIE development stages, fuzzy model design, system implementation, functional and usability testing, and a discussion that interprets these findings against the three research aims stated in Section 1.

3.1 Fuzzy Model and Rule Base Design

Table 1 summarizes the membership-function parameters adopted for the three input variables and the output variable, together with the rationale for each boundary.

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Table 1. Membership Function Parameters

Variable	Set	Shape [parameters]	Rationale
Attendance (X1)	Low	Trapezoidal [60, 75]	75% is the school's minimum attendance threshold
	Medium	Triangular [60, 75, 90]	Peaks at the critical 75% threshold
	High	Trapezoidal [85, 95]	≥ 95% regarded as full attendance
Behavior points (X2)	Low	Trapezoidal [40, 60]	Below the escalation threshold in the school SOP
	Medium	Triangular [40, 60, 80]	Range still considered remediable
	High	Trapezoidal [60, 85]	Above the neutral initial score of 75
Peer score (X3)	Low	Trapezoidal [50, 70]	Below-average peer rating (≈ 2.5–3.5 / 5)
	Medium	Triangular [50, 75, 90]	Peaks at an average rating of 3.75 / 5
	High	Trapezoidal [80, 95]	≥ 4 / 5 average peer rating
Output score (Z)	Needs Guidance	Trapezoidal [40, 50]	Z* < 55 signals need for formal intervention
	Fair	Triangular [40, 55, 70]	Transition band between guidance and positive rating
	Good	Triangular [65, 80, 90]	Above-average behavior, no escalation required
	Excellent	Trapezoidal [85, 95]	Z* ≥ 85 qualifies for formal appreciation

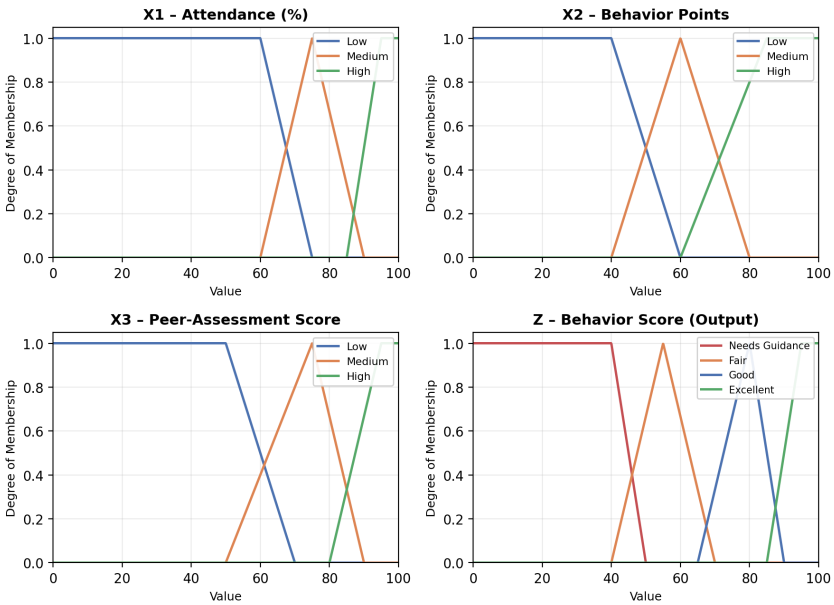

Figure 2. Membership functions for variables X1 (attendance), X2 (behavior points), X3 (peer-assessment score), and output Z (behavior score)

Adjacent sets were deliberately designed to overlap, for instance the Low and Medium sets of X1 both carry non-zero membership between 60 and 75, so that every possible input value activates at least one rule and the inference engine never returns an undefined output. With three linguistic sets per input variable, the rule base contains $3^3 = 27$ combinations, shown in full in Table 2.

Table 2. Complete 27-Rule Mamdani Rule Base

No.	Attendance (X1)	Points (X2)	Peer Score (X3)	Output (Z)
1	High	High	High	Excellent

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No.	Attendance (X1)	Points (X2)	Peer Score (X3)	Output (Z)
2	High	High	Medium	Excellent
3	High	High	Low	Good
4	High	Medium	High	Excellent
5	High	Medium	Medium	Good
6	High	Medium	Low	Fair
7	High	Low	High	Good
8	High	Low	Medium	Fair
9	High	Low	Low	Needs Guidance
10	Medium	High	High	Excellent
11	Medium	High	Medium	Good
12	Medium	High	Low	Fair
13	Medium	Medium	High	Good
14	Medium	Medium	Medium	Fair
15	Medium	Medium	Low	Needs Guidance
16	Medium	Low	High	Fair
17	Medium	Low	Medium	Needs Guidance
18	Medium	Low	Low	Needs Guidance
19	Low	High	High	Good
20	Low	High	Medium	Fair
21	Low	High	Low	Needs Guidance
22	Low	Medium	High	Fair
23	Low	Medium	Medium	Needs Guidance
24	Low	Medium	Low	Needs Guidance
25	Low	Low	High	Needs Guidance
26	Low	Low	Medium	Needs Guidance
27	Low	Low	Low	Needs Guidance

The consequent of each rule follows two design principles agreed with the school counselor. The first is dominance, when all three inputs fall in the same category, the output mirrors that category in full, as in Rule 1 (all High = Excellent) and Rule 27 (all Low = Needs Guidance). The second is compensation, strength on one or two dimensions can proportionally offset weakness elsewhere. Rule 19 (X1 Low, X2 High, X3 High = Good) reflects the judgment that a student with low attendance but a strong formal-behavior record and strong peer rating should not automatically be classified as needing guidance, while Rule 9 (X1 High, X2 Low, X3 Low = Needs Guidance) confirms that high attendance alone is insufficient when the other two dimensions are both weak.

A systematic audit of all 27 rules shows that this compensation mechanism is a consistent pattern rather than an isolated case. Fifteen of the 27 combinations have Attendance (X1) or Behavior Points (X2) rated Low, of these, six (40%) still avoid the Needs Guidance category because the Peer Score (X3) is Medium or High, listed in Table 3. In every one of these six rules, X3 is never Low, confirming its role as the most consistent “rescue” factor. Conversely, every rule with two or more Low-

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rated dimensions (Rules 9, 18, 21, 24, 25, 26, 27) resolves to Needs Guidance without exception, showing that compensation is bounded, an advantage on one dimension can lift a weakness on one other dimension, but not on two simultaneously.

Table 3. Compensation Rules within the 27-Rule Base

Rule	X1	X2	X3	Output	Dimension Compensated
7	High	Low	High	Good	Behavior Points (X2)
8	High	Low	Medium	Fair	Behavior Points (X2)
16	Medium	Low	High	Fair	Behavior Points (X2)
19	Low	High	High	Good	Attendance (X1)
20	Low	High	Medium	Fair	Attendance (X1)
22	Low	Medium	High	Fair	Attendance (X1)

For each activated rule n, the firing strength αn is obtained with the MIN operator over the three input membership degrees, as in Equation (1). Rules sharing the same consequent are then combined with the MAX operator to form the aggregated output fuzzy set μsf, as in Equation (2). The crisp score Z* is finally obtained by discrete centroid defuzzification over zi, i = 1...n sample points on the output universe, as in Equation (3).

$$\alpha n = \min(\mu Attendance(x1), \mu Points(x2), \mu PeerScore(x3)) \quad (1)$$
$$\mu sf(z) = \max(\alpha 1, \alpha 2, \ldots, \alpha n) \quad (2)$$

$$Z^* = \Sigma_i\, zi \cdot \mu(zi) \,/\, \Sigma_i\, \mu(zi) \quad (3)$$

A manual worked example illustrates the compensation mechanism numerically. For inputs X1 = 82 (High), X2 = 70 (Medium-High boundary), and X3 = 85 (High), the engine returns Z* = 71.28, which is classified Good, not a binary pass/fail outcome, demonstrating that a student with an imperfect behavior-point score can still be rated positively once attendance and peer standing are strong enough to compensate.

3.2 System Architecture and Implementation

The relational schema underlying SiPandu comprises 21 tables grouped into six functional domains, user profiles, academic period/class management, attendance (X1), behavior points (X2), peer review (X3), and the fuzzy configuration and final-score tables, illustrated in Figure 3. Three database triggers keep derived values consistent regardless of which client performed the write, one recalculates each student's cumulative raw behavior-point balance on every transaction insert, soft delete, or restore, one aggregates all submitted peer ratings into the X3 score the moment a homeroom teacher closes a review session, and one maintains audit timestamps. Critical computations are pushed into the database layer specifically so that they cannot be bypassed by direct client access, complementing the RLS policies described in Section 3.3.

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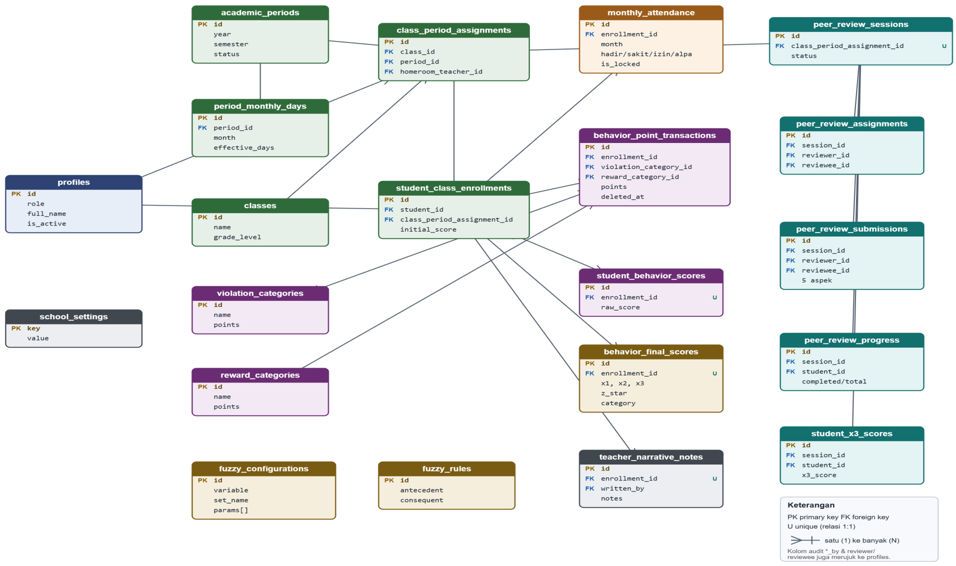

Figure 3. ERD of the database, comprising 21 tables across six functional domains (user, academic, attendance, behavior points, peer review, and fuzzy inference).

On top of this schema, three role-specific modules were implemented. The Administrator module manages master data (academic periods, classes, teacher assignments) and exposes a live Fuzzy Configuration page (Figure 6) where an authorized staff member can edit membership-function parameters and the 27-rule consequents, with the membership curves and simulator updating in real time, this reconfigurability directly answers the third literature gap identified in Section 1. The Homeroom Teacher module handles monthly attendance entry with a month-locking mechanism, behavior-point transactions, peer-review session management, and a results dashboard (Figure 4) that lists X1, X2, X3, Z*, and category for every student in the class, with PDF and Excel export. The student module is limited to viewing one's own score history and completing the peer-assessment questionnaire, anonymity is enforced not only at the interface level but structurally, the RLS policy on the submission table blocks all SELECT operations for the student role, including on a student's own submitted rows, so that reviewer identity cannot be recovered even by the reviewer.

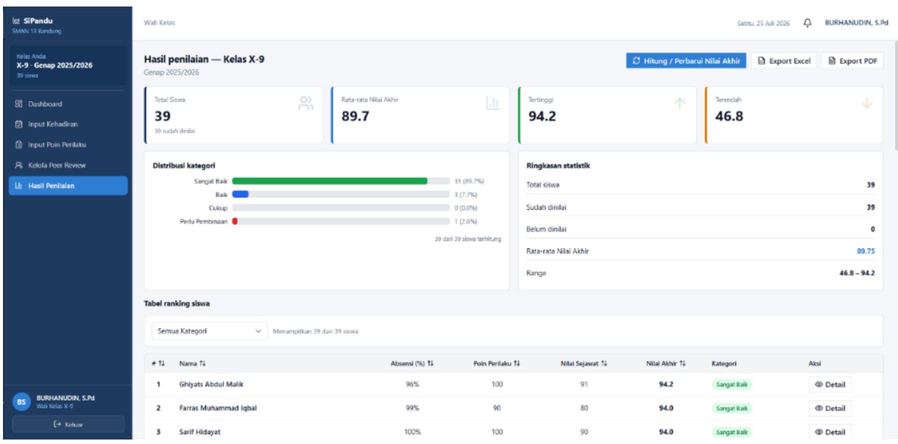

Figure 4. Homeroom teacher's final-assessment dashboard, listing attendance (X1), behavior points (X2), peer score (X3), the fuzzy output Z*, and category for every student.

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The gamification layer computes seven achievement badges automatically from each student's Z* history and point-transaction log, six outcome badges (Perfect Attendance, Achievement, Active Collaborator, Behavior Star, Consistent Improvement, and Role Model) and one participation badge (Active Reviewer), awarded the moment a student completes all five assigned peer reviews and shown as immediate feedback on the confirmation screen (Figure 5). Presenting the participation badge immediately after submission, rather than only in a later summary, follows evidence that adolescents respond more strongly to prompt, concrete recognition than to delayed or abstract praise [15].

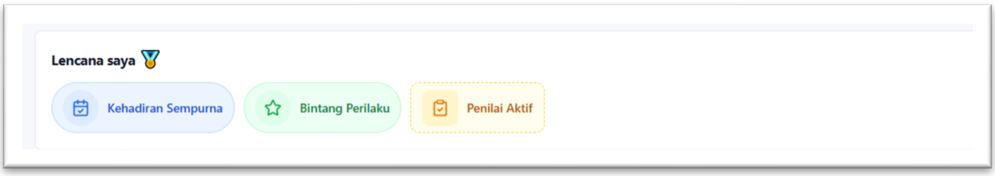

Figure 5. Achievement badges displayed on the student dashboard, including the Active Reviewer badge shown as immediate feedback after peer-review submission.

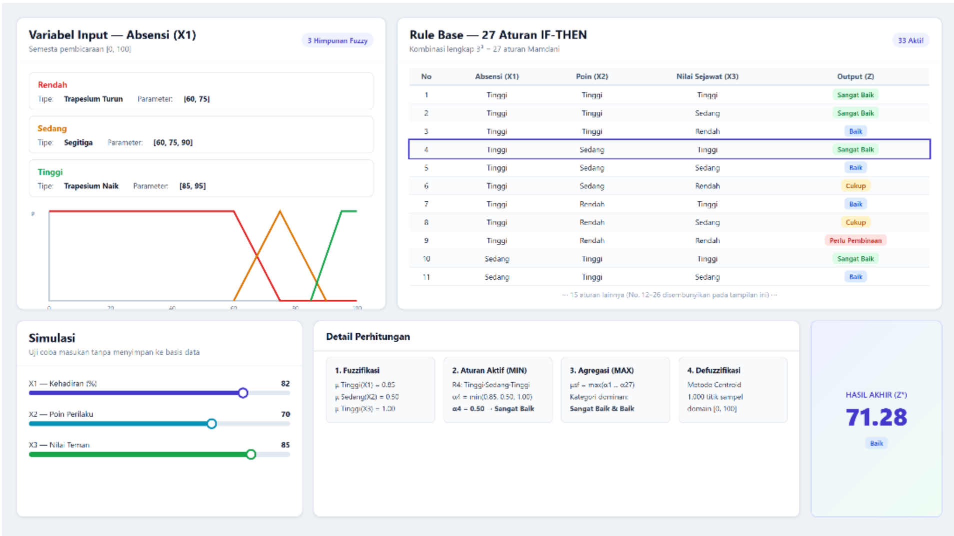

Figure 6. Fuzzy Configuration page in the Administrator module, showing editable membership-function curves, the 27-rule consequent table, and a live Z* simulator.

As shown in Figure 6, the interface couples three panels in a single view, an editable membership-function curve for the selected variable, the 27-rule consequent table, and a live simulator that recomputes Z* as parameters change. This lets an authorized staff member preview the effect of a boundary adjustment before committing it for instance, if the school later revises its official minimum-attendance threshold, the Low and Medium parameters of Attendance (X1) in Table 1 can be edited directly through this page, with the resulting shift in Z* visible immediately in the simulator panel. This live configuration loop is what operationalizes the reconfigurability introduced in Section 1, unlike the fixed-parameter simulation tools used in prior fuzzy education research [5], recalibration in SiPandu happens through the production application itself, without touching source code.

3.3 Functional and Security Testing (Black-Box)

Table 4 summarizes the 20 black-box scenarios executed against the production deployment. All 20 scenarios (BB-01 to BB-20) produced the expected output, a 100% success rate that verifies all 13 functional requirements and the RLS-related non-functional requirement.

Table 4. Black-Box Testing Results (Selected Scenarios)

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Code	Test Scenario	Expected Result	Result
BB-01/02	Login with valid / invalid credentials per role	Redirected per role, error message on invalid attempt	Pass
BB-06	Bulk student import from Excel	Data saved in a single atomic transaction	Pass
BB-07/08	Edit membership-function parameters and rule consequents	Curves and simulator update, parameters persist	Pass
BB-09	Simulate X1, X2, X3 in the fuzzy simulator	Z* and category shown without persisting to the database	Pass
BB-12/13	Attendance entry with month lock, point transaction with soft delete	Data saved, lock/unlock works, raw_score updates via trigger	Pass
BB-14/15	Open/close peer-review session, verify X3 aggregation	Status changes, X3 computed correctly on session close	Pass
BB-17	Student submits peer review, verify anonymity	Submission saved, reviewer identity not exposed	Pass
BB-19	Homeroom teacher edits the student-id (UUID) in the URL to access another class	Row not returned by RLS, application renders a 404 page	Pass
BB-20	Verify a student cannot request another student's data	No route or parameter exists to request another student's data, all queries are bound to the authenticated session and enforced by RLS	Pass

Scenarios BB-19 and BB-20 specifically verify that PostgreSQL Row Level Security prevents cross-actor data leakage. RLS behaves as a silent filter at the database level, a row that does not belong to the requesting user is not returned rather than explicitly rejected, so unauthorized access is invisible instead of announced. On the homeroom-teacher side, the only URL parameter that could be manipulated is an unguessable UUID identifying a student-detail page, substituting the UUID of a student from another class returns an empty row set, which the application renders as a standard 404 page rather than a distinguishable "access denied" message, avoiding the information leak of confirming that a targeted record exists. On the student side, no route or parameter accepts another student's identifier at all, since the student's own identity is derived from the authenticated session (auth.uid()) rather than from any client-supplied value, so there is no channel through which a student could even attempt to request another student's record.

3.4 Field Trial and Usability Evaluation

The fuzzy model was applied to one full semester of real attendance, behavior-point, and peer-assessment data for the 39-student implementation sample. Table 5 shows the resulting category distribution. The class mean was Z* = 89.75 (maximum 94.2, minimum 46.8), 35 of 39 students (89.7%) were classified Excellent, 3 (7.7%) Good, and 1 (2.6%) Needs Guidance, a student the system correctly flagged as requiring further attention from school staff.

Table 5. Distribution of Final Behavior Scores (Class X-9, n = 39)

Category	Z* Range	Students	Percentage
Excellent	$Z^* \geq 85$	35	89.7%
Good	$70 \leq Z^* < 85$	3	7.7%
Fair	$55 \leq Z^* < 70$	0	0%
Needs Guidance	$Z^* < 55$	1	2.6%

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Category	Z* Range	Students	Percentage
Total	–	39	100%

Usability was evaluated using the SUS questionnaire described in Section 2.3. Table 6 summarizes the mean score by respondent group. The overall mean across all 17 respondents was 65.88, categorized as OK/Marginal, slightly below the commonly cited global SUS benchmark of 68 [17]. Disaggregating by role, however, reveals a substantial gap: the two administrative respondents (Admin and homeroom teacher) averaged 92.5, in the Excellent range, while the 15 student respondents averaged only 62.33.

Table 6. System Usability Scale (SUS) Score by Respondent Group

Respondent Group	n	Mean SUS Score	Category
Admin	1	95.0	Best Imaginable
Homeroom Teacher	1	90.0	Excellent
Student	15	62.33	OK / Marginal
Overall	17	65.88	OK / Marginal

Item-level analysis clarifies which aspect of usability drives this gap. Following the two-factor structure Lewis and Sauro [18] identified for the SUS instrument, items 4 ("I would need technical support to use this system") and 10 ("I needed to learn a lot before I could get going with this system") load onto a distinct Learnability factor, separate from the eight-item Usability factor. Table 7 summarizes the three items most relevant to this gap.

Table 7. SUS Items Most Relevant to the Usability Learnability Gap

Item	Statement	Factor	Mean (1–5)	% of Max. Contribution
5	"I thought the functions in this system were well integrated"	Usability	4.18	79.5% (highest)
4	"I would need technical support to use this system"	Learnability	2.88	53.0% (2nd lowest)
10	"I needed to learn a lot before I could get going with this system"	Learnability	3.41	39.8% (lowest)

This pattern indicates that SiPandu's core functionality is not in question, respondents consistently agreed the system works as intended, but that first-time users, predominantly students exposed to the system for a single 10–15 minute demonstration, had not yet climbed the learning curve at the time of evaluation.

Because the deficit is specifically in learnability rather than core functionality, three concrete interventions follow from this diagnosis. First, a short-guided walkthrough triggered on first login for the student role would substitute structured exposure for the repeated incidental use administrative users already accumulate through daily operation. Second, embedding contextual tooltips on the score-history and peer-review screens would let first-time student users interpret Z*-related terminology, such as category labels and badge criteria, without external explanation. Third, a low-stakes sandbox mode allowing students to submit a practice peer review before the graded session would convert passive demonstration into active, low-risk exposure. None of these interventions require redesigning the underlying interface, consistent with the finding that the gap reflects exposure rather than interface defects.

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3.5 Comparative Evaluation with Fuzzy Sugeno and Fuzzy Tsukamoto

To empirically justify the choice of Mamdani inference over alternative methods, the same 27-rule base and input membership functions were used to compute Z* for all 39 students under zero-order Sugeno and Tsukamoto inference (see Section 2.3 for the consequent-mapping procedure). Table 8 summarizes the comparison.

Table 8. Comparison of Mamdani, Sugeno, and Tsukamoto Inference (n = 39)

Method	Class Mean Z*	Mean Abs. Diff. from Mamdani	Correlation with Mamdani	Category Agreement with Mamdani
Mamdani (published)	89.75	-	-	-
Sugeno (zero-order)	92.55	2.80	0.966	94.9% (37/39)
Tsukamoto	86.45	3.55	0.985	84.6% (33/39)

All three methods correlate strongly ($r > 0.96$), confirming the 27-rule design in Table 2 drives consistent classifications regardless of inference method, a sign that the rule base is robust to the specific defuzzification mechanism rather than an artifact of Mamdani's centroid calculation alone. Category-level agreement, however, reveals a systematic pattern: all disagreements between Mamdani and both alternative methods occur for students whose Z* falls within roughly three points of a classification boundary (55, 70, or 85 in Table 5); no case shifted a student across more than one category. Sugeno produced a systematically higher class mean because its singleton consequents sit at each category's peak or plateau boundary, discarding the partial-membership blending Mamdani's centroid preserves when adjacent output sets overlap, consistent with Sugeno's known tendency toward sharper, less-smoothed outputs [12]. Tsukamoto produced a systematically lower class mean because its rising-ramp representation of the two triangular categories caps achievable output below each category's own peak unless firing strength reaches 1.0, a structural consequence of adapting Tsukamoto's monotonicity requirement to a non-monotonic Mamdani-derived output design, rather than evidence that Tsukamoto is miscalibrated. These results support the method choice made in Section 1: Mamdani's centroid defuzzification yields outputs strongly consistent with both alternatives ($r > 0.96$) while preserving the fully interpretable, linguistically labeled output a non-technical homeroom teacher need.

3.6 Discussion

The three research aims stated in Section 1 are addressed directly by the findings above. First, the integration of objective school-observation data (X1, X2) with subjective peer-assessment data (X3) into one adaptive score was achieved by standardizing all three variables to a shared [0,100] universe and validating the otherwise subjective X3 instrument through the school counselor's expert judgment rather than through statistical psychometrics, an appropriate scope for a software-engineering R&D study rather than a psychometric one. Second, the adaptive rule base answers the need for proportional weighting identified in Section 1, the systematic compensation pattern documented in Table 3, six of fifteen Low-attendance-or-points combinations rescued by a strong peer score, but never when two dimensions are simultaneously weak, shows that SiPandu's adaptiveness is a designed, auditable property of the rule base rather than an emergent side effect. This directly extends prior Mamdani applications in Indonesian educational assessment [3], [4], which demonstrated that fuzzy inference outperforms deterministic scoring but did not examine the internal consistency of their own rule bases at this level of granularity.

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Third, the black-box and usability results together indicate that the DSS was implemented and is functionally reliable, while also surfacing a concrete adoption risk, usability is uneven across user roles. This pattern echoes findings on school management information systems, where administrative users with repeated exposure report substantially higher usability satisfaction than intermittently exposed users [19], reinforcing that the gap observed here is a general onboarding phenomenon in school software rather than a defect specific to SiPandu's student interface.

Compared with the fixed-parameter simulation approach common in prior fuzzy education studies [5], SiPandu's Fuzzy Configuration module allows the school to recalibrate membership functions and rule consequents through its own interface whenever its behavioral SOP changes, without touching source code, directly closing the third literature gap identified in Section 1. The fuzzy rule base and peer-assessment instrument were content-validated by the school's guidance counselor (Guru BK), the domain expert directly responsible for behavioral-assessment policy at the partner school, during the Analysis phase of the ADDIE cycle (Section 2). This expert reviewed and confirmed both the five X3 dimensions and the complete 27-rule consequent table prior to implementation, grounding the otherwise subjective X3 variable and the compensation logic in Table 3 in expert judgment rather than arbitrary parameter choices.

However, several limitations bound the interpretation of these results. The field trial was limited to a single class at a single school, so the category distribution and usability figures cannot yet be generalized to other classes or institutions with different behavioral baselines. This limitation is not merely a matter of sample size: the membership-function boundaries in Table 1 were anchored to this school's specific attendance and disciplinary thresholds, so a school with different institutional norms would likely require recalibrating these parameters, precisely the workflow the Fuzzy Configuration module is designed to support, rather than assuming the published parameters transfer directly. The X3 instrument's validity rests on content validation by one domain expert rather than on construct-validity and reliability testing (e.g., Cronbach's alpha), which falls outside the scope of this software-engineering study but should precede any permanent, high-stakes adoption of the instrument. Finally, black-box testing was carried out by the same person who developed the system, independent third-party testing in future work would strengthen confidence in the functional results.

Beyond validating the technical design, the compensation pattern in Table 3 carries a substantive fairness implication: because the mechanism only ever offsets a single weak dimension and never two simultaneously, SiPandu structurally avoids the two failure modes common to additive point systems, being too lenient toward students weak across the board, or too punitive toward students who falter on only one otherwise-strong dimension. A homeroom teacher reviewing Figure 4 can trust that an Excellent or Good classification was never earned through one strong metric masking two weak ones, a guarantee the school's prior additive system could not offer.

4. CONCLUSION

This study designed and implemented SiPandu, a Fuzzy Mamdani-based Decision Support System that integrates objective school-observation data (attendance percentage X1 and cumulative behavior points X2) with a subjective peer-assessment score (X3) into a single adaptive student behavior score. The three variables were standardized to a shared [0,100] universe and processed through 27 dead-zone-free IF-THEN rules built on two explicit design principles, dominance and compensation, with discrete centroid defuzzification mapping the result to four categories: Needs Guidance, Fair, Good, and Excellent. An audit of the complete rule base confirmed that this compensation is a designed and bounded property rather than an incidental one: strength on one dimension can lift a weakness on one other dimension, but not on two simultaneously.

Implemented as a web-based prototype and trialled on one class at a public senior high school in Bandung, the system passed all functional test scenarios, including verification that role-based data isolation is enforced at the database level. Usability results were favorable among administrative users but markedly lower among students, a gap attributable to differences in exposure time rather than to interface defects, and one that points to onboarding rather than redesign as the appropriate corrective.

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The main benefit of this research is a reproducible template for combining objective and subjective behavioral indicators into one interpretable decision-support score, positioned deliberately as a recommendation tool for the homeroom teacher rather than an automated disciplinary system. However, the study has several limitations, the field trial covered only one class at one school, the peer-assessment instrument was validated through expert judgment rather than statistical psychometrics, and functional testing was conducted by the system's own developer.

A supplementary comparison against zero-order Fuzzy Sugeno and Fuzzy Tsukamoto inference on the same 39-student dataset confirmed that all three methods agree closely ($r > 0.96$), with category-level disagreements confined to students within roughly three points of a classification boundary, supporting Mamdani's suitability for this context without sacrificing consistency with numerically-oriented alternatives.

Future work should prioritize construct-validity and reliability testing (e.g., Cronbach's alpha) of the peer-assessment instrument before wider adoption, a staged rollout across additional classes and schools accompanied by structured student onboarding to close the observed learnability gap, independent third-party functional testing, a quasi-experimental longitudinal study measuring actual behavior change over at least one academic year, and extending the comparative benchmark performed in this study (Section 3.5) to Type-2 fuzzy or ANFIS approaches on a larger, multi-class dataset.

5. CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Ravindra Maulana Sahman: Conceptualization, Methodology, Software, Validation, Formal Analysis, Writing – Original Draft, Writing – Review & Editing. **Asep Wahyudin**: Investigation, Data Curation, Visualization. **Rani Megasari**: Supervision, Project Administration.

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During the writing process, the authors used Claude.AI for for translating the manuscript from Indonesian to English. The authors reviewed, verified, and revised the output generated by the AI tool and take full responsibility for the final content of the manuscript.

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