#### Review Article

# A Systematic Review and Meta-Analysis of Fuzzy Logic for Students' Performance Assessment

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Abstract - Assessment of students' performance using fuzzy logic provides high flexibility and reliability in education. This study aims to apply a systematic review and meta-analysis to synthesize the findings of selected studies in this field, with a focus on the effects of fuzzy logic system configurations on students' performance assessment outcomes, focusing on subgroup analyses to explore variations across input and output factors. A total of 109 articles were retrieved from databases, including ScienceDirect, Springer, IEEE, Scopus, and Google Scholar, for qualitative and quantitative syntheses. Among these, 46 studies reported both fuzzy and non-fuzzy median scores and were included in the meta-analysis. Results showed that output member functions achieved the highest median scores ( $\geq 89.50$ ), and subgroup analyses revealed significant heterogeneity across studies  $(I^2 \ge 75\%, p < 0.01)$ . Frequency-based combinations of fuzzy variables generally outperformed non-frequency configurations, enhancing system granularity and accuracy. These findings highlight the importance of optimizing fuzzy logic system designs to improve student performance assessment.

**Keywords** - Students' performance, Students' performance assessment, Fuzzy logic, Systematic review, Meta-analysis.

### 1. Introduction

Education increasingly relies on accurate and reliable methods to assess students' performance, as assessment plays a central role in guiding teaching practices and monitoring learning outcomes [1-7]. The results of assessments help students and parents understand the student's learning progress. Hence, assessing students' performance needs to capture the inherent complexity and variability. Currently, assessment methods still need to accurately reflect ambiguous outcomes, especially in assessing qualitative aspects (e.g., critical thinking and emotional engagement) [8-10]. These challenges highlight the need for more flexible and adaptive approaches that can handle ambiguity and uncertainty in performance evaluation.

Lotfi Zadeh introduced fuzzy logic in 1965, which has emerged as a viable alternative for interpreting uncertain or imprecise data [11]. There were various studies using fuzzy logic to assess students' performance, demonstrating its potential to produce more nuanced and reliable outcomes than conventional approaches. For example, fuzzy-based models have been used to integrate multiple variables (e.g., test scores, participation, skills) into holistic performance measures, overcoming the rigidity of traditional scoring

systems. Prior research has shown that fuzzy logic can adapt to diverse educational contexts, enhance decision-making, and capture hidden aspects of student performance that may otherwise be overlooked [7, 12-14].

Despite these promising findings, systematic evidence on the effectiveness of fuzzy logic in educational assessment remains limited. Amelia et al. conducted the first Systematic Review and Meta-Analysis (SRMA) in this field, highlighting positive effects of fuzzy logic methods on performance assessment [15]. While their study provided an important foundation by synthesizing multiple findings, it did not fully investigate how specific fuzzy logic system configurations such as the number of inputs, membership functions, rules, and outputs - influence overall assessment outcomes. Furthermore, no comprehensive meta-analysis to date has compared fuzzy and non-fuzzy approaches across a wide range of variables, leaving a significant gap in understanding the optimal conditions for applying fuzzy logic in education. The SRMA synthesizes findings from multiple studies, which offer a comprehensive overview and precise effect size estimates. By aggregating data from multiple studies, it increases the overall sample size, which improves the likelihood of detecting significant effects - especially those

that may have been missed in individual studies due to their smaller sample sizes [1, 2, 16]. However, no SRMA has synthesized multiple studies assessing scores using fuzzy logic to date.

To address this gap, the present study conducts an SRMA to evaluate the effectiveness of fuzzy logic-based systems in assessing student performance compared to traditional methods. While the previous review has provided valuable insights, this study explicitly examines how different frequency vs. configurations (e.g., non-frequency combinations of input and output variables) impact assessment outcomes, thereby offering deeper insights into the mechanisms driving fuzzy logic performance. By identifying which configurations yield the most consistent and effective results, this study contributes novel evidence to guide educators and researchers in optimizing fuzzy-based assessment models. The study is guided by the following research questions:

- RQ1: What are the publication trends and design characteristics of studies using fuzzy logic to assess students' performance?
- RQ2: How do fuzzy logic-based systems perform in student assessment compared to non-fuzzy approaches across varying input configurations?
- RQ3: What is the effect of the number and type of membership functions on assessment outcomes in fuzzy vs. non-fuzzy models?
- RQ4: How does the number of rules and outputs influence assessment performance in fuzzy and non-fuzzy logic systems?
- RQ5: Are there shared optimal configurations between fuzzy and non-fuzzy models in terms of output functions and membership settings?
- RQ6: What is the overall impact of fuzzy logic on student performance based on meta-analysis?
- RQ7: Which configurations (input/output variables, membership functions, and rule types) yield the most consistent and effective outcomes?

Conducting a meta-analysis allows for the systematic analysis and synthesis of the findings across multiple studies, providing a comprehensive overview of the effectiveness of different fuzzy logic approaches. Findings from this study may support educators and institutions in determining the most effective variables for affecting students' performance assessments.

#### 2. Materials and Methods

#### 2.1. Literature Search

The study collected research articles published from 2008 to 2024 with various databases: (1) ScienceDirect, (2) Springer, (3) IEEE, (4) Scopus, and (5) Google Scholar and

followed the PRISMA guideline [17] in conducting a systematic review. Boolean logic functions using "AND" and "OR" connectors were employed during the search process. Advanced search keywords utilized in ScienceDirect, Springer, IEEE, and Scopus were: ("student performance" OR "student performance assessment" OR "student performance evaluation") AND ("fuzzy logic"). In addition to the database searches, hand-searching was conducted on Google Scholar to identify additional articles that met the eligibility criteria, thus broadening the scope of the search.

#### 2.2. Publications Preference

The preference procedure for articles in the review involved three steps: title screening, abstract screening, and full-text assessment. The inclusion criteria required the articles to discuss the relevance of fuzzy logic in assessment, with a focus on collecting data from students' performance. Articles lacking sufficient information on fuzzy logic in assessment for students' performance were not included. Additionally, review articles, book chapters, theses, conference abstracts, letters, non-English articles, and duplicated articles across databases were also excluded from the review. These exclusion criteria aimed to ensure the relevance and quality of the selected studies.

To avoid bias in the procedure of article selection, a checklist related to the accuracy of data of studies provided by the Joanna Briggs Institute (JBI) is used [18]. Two independent reviewers assessed publications by using the checklist. Only studies that received a 'yes' answer for all questions were included in the review. In cases where there were discrepancies between the reviewers' assessments for any question, there is another assessment by a third independent reviewer. The consensus was reached by considering the agreement of 'yes' answers from at least two out of three reviewers, leading to the final inclusion decision for the studies.

To further ensure the integrity of included studies, only peer-reviewed journal articles with transparent and sufficiently detailed methodological reporting were considered. Studies with unclear methodologies, lacking transparency, or exhibiting potential biases were excluded to maintain the reliability of the evidence base.

#### 2.3. Data Extraction

The relevant information from each retrieved publication was collected and recorded in a Microsoft Excel 365 spreadsheet. The collected data included the following details: (1) year of publication, (2) first author, (3) sample size, (4) assessment scores (mean) and Standard Deviation (SD) values in both fuzzy and non-fuzzy logic approaches, (5) variables for the fuzzy logic approaches include (5.1) the number of inputs (Input: no. inputs), (5.2) the number of membership functions for the input (Input: no. member functions), (5.3) function category of the membership for the input (Input:

function category), (5.4) the number of rules (no. rules), (5.5) the number of outputs (Output: no. outputs), (5.6) the number of membership functions for the output (Output: no. member functions), (5.7) function category of the membership for the output (Output: function category). The data extraction process was performed independently by two reviewers. Subsequently, a third reviewer cross-checked the results. The data underwent a thorough review and were included in the analysis only after a consensus was reached among all reviewers. By employing this rigorous process, the collected data ensured reliability and reduced potential bias in the subsequent analysis.

#### 2.4. Statistical Analysis

Only studies that reported datasets of sample size, assessment scores, and SD values for both fuzzy logic (the experimental group) and non-fuzzy logic (the control group) were used in the meta-analysis. Standardized Mean Differences (SMD, Hedge's g) and 95% confidence intervals (CI) were calculated using a random-effects model to account for between-study heterogeneity. Heterogeneity among the selected studies was assessed using the inverse variance index ( $I^2$ ), with an index greater than or equal to 75.0% and heterogeneity is considered significant if a p-value less than 0.05 is considered an indicator of significant heterogeneity. Differences among the selected studies in subgroups were

assessed using the chi-squared ( $\chi^2$ ), where a chi-squared value greater than 0 and a p-value less than 0.05 were considered indicators of significant differences [19-22]. The results of the meta-analysis were represented using forest plots [23]. The R programming language in RStudio, along with the "meta" and "meta for" packages, was employed for the meta-analysis and subgroup analyses.

#### 3. Results

#### 3.1. Characteristics of Selected Studies

A total of 5,757 articles were initially identified for potential inclusion in the study. After excluding non-research articles (n=1,988) and duplicated articles (n = 2,287) based on evaluating titles and abstracts, 1,482 articles remained. Next, 1,482 articles were further excluded as they did not involve an assessment of student performance using fuzzy logic (n = 865), and full texts were unavailable (n = 508). This left a final selection of 109 articles for the systematic review. Within the 109 selected articles, data on assessing students' performance and containing results were specifically focused on. Consequently, a subset of 46 articles was used for the subsequent meta-analysis. The study selection process adhered to the PRISMA flow diagram, depicted in Figure 1. This systematic approach ensured a thorough and transparent selection process, followed established guidelines, and resulted in a robust set of articles for analysis.

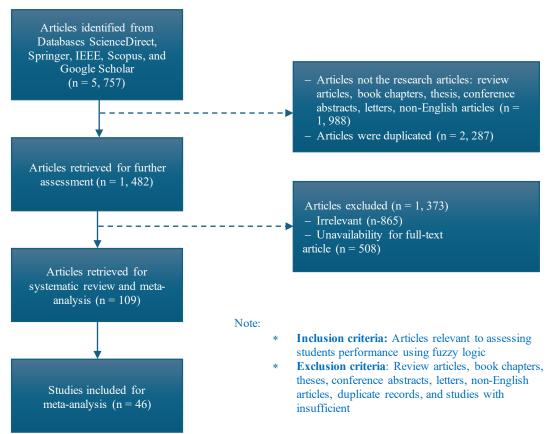


Fig. 1 PRISMA workflow for choosing publications

• RQ1: What are the publication trends and design characteristics of studies using fuzzy logic to assess students' performance?

More than half of the 109 studies included were published between 2020 and 2024 (52.29%), with the majority being articles (51.38%). The studies were predominantly conducted with 2, 3, and 4 input variables, accounting for 16.51%, 28.44%, and 19.27% of the total. Similarly, most studies used 3, 4, and 5 membership functions for the inputs, at 28.44%, 12.84%, and 27.52%, respectively.

The most common membership function categories were triangular (41.28%), trapezoidal (11.93%), and hybrid (25.69%). In terms of outputs, nearly all studies (94.50%) focused on a single output. 30.28% of the studies used five membership functions for the output membership functions.

The triangular (39.45%) and trapezoidal (15.60%) functions were the most frequently applied categories (Table 1).

# 3.2. Associations between Variables and Assessment Scores based on Fuzzy and Non-Fuzzy

Among 109 selected studies, fuzzy-based assessments consistently demonstrated higher flexibility and adaptability in specific configurations. From the results of analyzing assessment scores across studies using fuzzy and non-fuzzy methods, ten-input fuzzy systems achieved an impressive top median score of 74.10 (IQR 38.42–76.07), outperforming non-fuzzy methods, which peaked at 72.21 (IQR 62.80–83.87) with four inputs. Similarly, fuzzy models with twelve input member functions reached a remarkable median score of 74.10 (IQR 74.10–74.10), while non-fuzzy systems delivered their best performance of 73.10 (IQR 73.10–73.10) with seven functions.

Table 1. Characteristics of selected studies for systematic review (n = 109)

			d studies for system Publication	Publication Year							
Characteristics	No. Studies	Article Conference		2009-2014	2015-2019	2020-2024					
	n (%)	56 (51.38)	53 (48.62)	17 (15.60)	35 (32.11)	57 (52.29)					
Input: No. Inputs*											
1	7 (6.42)	3 (2.75)	4 (3.67)	ı	3 (2.75)	4 (3.67)					
2	18 16.51)	9 (8.26)	9 (8.26)	4 (3.67)	6 (5.50)	8 (7.34)					
3	31 28.44)	16 14.68)	15 (13.76)	5 (4.59)	8 (7.34)	18 (16.51)					
4	21 19.27)	12 11.01)	9 (8.26)	1 (0.92)	7 (6.42)	13 (11.93)					
5	13 11.93)	6 (5.50)	7 (6.42)	5 (4.59)	4 (3.67)	4 (3.67)					
6	7 (6.42)	3 (2.75)	4 (3.67)	1 (0.92)	1 (0.92)	5 (4.59)					
7	3 (2.75)	2 (1.83)	1 (0.92)	-	2 (1.83)	1 (0.92)					
8	3 (2.75)	3 (2.75)	-	-	1 (0.92)	2 (1.83)					
10	3 (2.75)	-	3 (2.75)	1 (0.92)	2 (1.83)	-					
12	1 (0.92)	1 (0.92)	-	-	1 (0.92)	-					
13	1 (0.92)	-	1 (0.92)	-	-	1 (0.92)					
17	1 (0.92)	1 (0.92)	-	-	-	1 (0.92)					
	Input: No. Member functions										
2	6 (5.50)	4 (3.67)	2 (1.83)	1 (0.92)	1 (0.92)	4 (3.67)					
3	31 (28.44)	18 (16.51)	13 (11.93)	4 (3.67)	6 (5.50)	21 (19.27)					
4	14 (12.84)	4 (3.67)	10 (9.17)	1 (0.92)	6 (5.50)	7 (6.42)					
5	30 (27.52)	16 (14.68)	14 (12.84)	6 (5.50)	15 (13.76)	9 (8.26)					
6	2 (1.83)	2 (1.83)	-	2 (1.83)	-	-					
7	1 (0.92)	-	1 (0.92)	-	-	1 (0.92)					
8	2 (1.83)	1 (0.92)	1 (0.92)	-	-	2 (1.83)					
9	2 (1.83)	-	2 (1.83)	-	1 (0.92)	1 (0.92)					
11	1 (0.92)	-	1 (0.92)	-	1 (0.92)	-					
12	1 (0.92)	-	1 (0.92)	1 (0.92)	-	-					
2 & 3	2 (1.83)	1 (0.92)	1 (0.92)	-	-	2 (1.83)					
3 & 4	3 (2.75)	3 (2.75)	-	-	1 (0.92)	2 (1.83)					
3 & 5	4 (3.67)	3 (2.75)	1 (0.92)	-	1 (0.92)	3 (2.75)					
3 & 8	1 (0.92)	-	1 (0.92)	-	1 (0.92)	-					
4 & 5	2 (1.83)	1 (0.92)	1 (0.92)	-	<u>-</u>	2 (1.83)					
5 & 6	1 (0.92)	-	1 (0.92)	-	-	1 (0.92)					
Not specified	6 (5.50)	3 (2.75)	3 (2.75)	2 (1.83)	2 (1.83)	2 (1.83)					
	Input: Function category										

45 41.28) 13 11.93) 10 (9.17) 28 25.69) 1 (0.92) 12 11.01)	19 (17.43) 7 (6.42) 7 (6.42) 16 (14.68)	26 (23.85) 6 (5.50) 3 (2.75) 12 (11.01)	5 (4.59) 2 (1.83) 3 (2.75) 4 (3.67)	15 (13.76) 3 (2.75) 5 (4.59) 6 (5.50)	25 (22.94) 8 (7.34) 2 (1.83)
10 (9.17) 28 25.69) 1 (0.92) 12 11.01)	7 (6.42) 16 (14.68)	3 (2.75) 12 (11.01)	3 (2.75)	5 (4.59)	2 (1.83)
28 25.69) 1 (0.92) 12 11.01)	16 (14.68)	12 (11.01)	ì	, ,	Ì
1 (0.92) 12 11.01)	-	` ′	4 (3.67)	6 (5 50)	_
12 11.01)	-	1 (0.02)		0 (3.30)	18 (16.51)
/	_ // /- /	1 (0.92)	-	-	1 (0.92)
	7 (6.42)	5 (4.59)	3 (2.75)	6 (5.50)	3 (2.75)
Outputs	, ,	, ,	, ,	, ,	1
3 (94.50)	54 (49.54)	49 (44.95)	15 (13.76)	34 (31.19)	54 (49.54)
2 (1.83)	1 (0.92)	1 (0.92)	1 (0.92)	1 (0.92)	-
2 (1.83)	-	2 (1.83)	=	=	2 (1.83)
1 (0.92)	1 (0.92)	=	=	=	1 (0.92)
1 (0.92)	-	1 (0.92)	1 (0.92)	-	-
er functions					
	2 (1.83)	1 (0.92)	1 (0.92)	=	2 (1.83)
19 17.43)		/	\ /	4 (3.67)	11 (10.09)
12 11.01)					4 (3.67)
33 30.28)	\ /	\ /		\ /	16 (14.68)
6 (5.50)					2 (1.83)
/	-	`	-	=	2 (1.83)
/	2 (1.83)		=	2 (1.83)	3 (2.75)
/	-		=	=	2 (1.83)
	-	/	=	1 (0.92)	-
1 (0.92)	-	` ′	-	-	1 (0.92)
1 (0.92)	1 (0.92)	-	1 (0.92)	-	-
24 22.02)	15 (13.76)	9 (8.26)	4 (3.67)	6 (5.50)	14 (12.84)
Function cat	egory	`			
43 (39.45)	18 (16.51)	25 (22.94)	5 (4.59)	14 (12.84)	24 (22.02)
17 15.60)		· /	2 (1.83)	6 (5.50)	9 (8.26)
7 (6.42)	5 (4.59)	2 (1.83)	\ /	4 (3.67)	1 (0.92)
14 (12.84)	9 (8.26)	5 (4.59)	2 (1.83)	4 (3.67)	8 (7.34)
1 (0.92)	-	1 (0.92)	-	-	1 (0.92)
27 (24.77)	17 15.60)	10 (9.17)	6 (5.50)	7 (6.42)	14 (12.84)
2 1 1 1	2 (1.83) 2 (1.83) 1 (0.92) 1 (0.92) er functions 3 (2.75) 19 17.43) 12 11.01) 33 30.28) 6 (5.50) 2 (1.83) 5 (4.59) 2 (1.83) 1 (0.92) 1 (0.92) 24 22.02) Function cat 3 (39.45) 17 15.60) 7 (6.42) 4 (12.84) 1 (0.92) 27 (24.77)	2 (1.83)	2 (1.83)	2 (1.83)	2 (1.83)

\* No. Inputs: 1 with 7 studies [24-30]; 2 with 18 studies [3, 5, 8, 31-45]; 3 with 31 studies [10, 45-74]; 4 (21) [75-95]; 5 with 13 studies [66, 96-107]; 6 with 7 studies [38, 65, 108-112]; 7 with 3 studies [113-115]; 8 with 3 studies [116-118]; 10 with 3 studies [119-121]; 12 with 1 study [122]; 13 with 1 study [123]; 17 with 1 study [124].

When exploring function categories, fuzzy methods excelled in the hybrid category, achieving a leading median score of 56.12 (IQR 20.66–76.05), whereas non-fuzzy methods saw their highest score with triangular functions at 56.12 (IQR 35.71–74.36). For the number of rules, fuzzy assessments with 58 rules scored a strong 82.11 (IQR 78.19–86.02), but non-fuzzy systems with 55 rules took the lead with an impressive 86.40 (IQR 86.40–86.40).

Interestingly, in assessments involving outputs, fuzzy systems with three outputs peaked at 69.15 (IQR 69.15–69.74), while non-fuzzy methods outperformed with the same number of outputs, scoring 86.40 (IQR 86.40–86.40). The type of output functions also revealed notable differences: trapezoidal functions dominated fuzzy and non-fuzzy methods, scoring 60.72 (IQR 6.74–76.05) and 60.45 (IQR 4.20–66.95), respectively. In addition, the number of output

member functions (eight functions) highlighted a shared strength across both methods of assessments (fuzzy and nonfuzzy), with the highest scores of 89.50 (IQR 47.44–89.72) and 89.74 (IQR 47.20–90.62), respectively.

These findings offer a compelling view of how different configurations shape assessment outcomes, underscoring the versatility of fuzzy logic. These results are visually depicted in the boxplots in Figure 2, illustrating the distribution and performance trends for a more precise understanding.

From the results, the answers for research questions (RQ2 to RQ5) are as follows:

• RQ2: How do fuzzy logic-based systems perform in student assessment compared to non-fuzzy approaches across varying input configurations?

Fuzzy systems consistently demonstrated higher adaptability in complex configurations. Systems with ten inputs achieved a top median score of 74.10, outperforming non-fuzzy methods that peaked at 72.21 with only four inputs. This suggests that fuzzy logic performs better with increased dimensionality.

 RQ3: What is the effect of the number and type of membership functions on assessment outcomes in fuzzy and non-fuzzy models?

Fuzzy systems with twelve membership functions achieved a median score of 74.10, higher than non-fuzzy systems' best of 73.10 (with seven functions).

Hybrid membership functions led fuzzy models to peak at 56.12, outperforming triangular functions used in non-fuzzy models with similar median scores but broader IQRs.

 RQ4: How does the number of rules and outputs influence assessment performance in fuzzy and non-fuzzy logic systems?

In fuzzy systems, using 58 rules led to strong performance (82.11), though non-fuzzy systems with 55 rules slightly outperformed them (86.40).

For outputs, fuzzy systems with three outputs achieved 69.15, whereas non-fuzzy systems with the same configuration reached a higher 86.40, suggesting an advantage for non-fuzzy logic in multi-output setups.

• RQ5: Are there shared optimal configurations between fuzzy and non-fuzzy models in terms of output functions and membership settings?

Both methods achieved their highest scores with eight output membership functions, with fuzzy systems reaching 89.50 and non-fuzzy models scoring slightly higher at 89.74, indicating that this configuration is effective across both paradigms.

### 3.3. Meta-Analysis for Chosen Studies

46 studies from the 109 studies provided data on assessment scores (mean), Standard Deviations (SD), and component-related information concerning students' performance with both fuzzy and non-fuzzy logic were included in the meta-analysis.

Configurations of variables in the input and output, including frequency-based and non-frequency-based setups, were combined to form subgroups in the meta-analysis. Values of a variable with total studies exceeding 10% were classified as frequency configurations. For example, the total studies with 2 inputs accounted for 16.51%, so 2 inputs were

considered a frequency configuration. The meta-analysis highlighted the impact of different configurations of fuzzy logic systems on the assessment of student performance.

For combinations of three variables (no. inputs, no. membership functions, and function categories), heterogeneity across studies was significant (P=78%, p<0.01), with a slight overall effect size (Hedges' g = 0.17). Subgroup analyses showed that frequency-based configurations generally yielded more consistent results.

Specifically, the combination of frequency-based inputs and membership functions with frequency-based function categories resulted in a moderate effect size (Hedges' g = 0.60, P = 68%, p < 0.01).

In contrast, non-frequency-based configurations often produced inconsistent results, with one subgroup achieving a very high heterogeneity (P=90%, Hedges' g=0.91). For combinations of four variables (no. inputs, no. membership functions, function categories, and no. rules), including rules that increased the complexity but did not substantially improve overall outcomes.

Frequency-based configurations, especially with non-frequency rules, yielded the most favourable results (Hedges' g = 0.60, P = 68%).

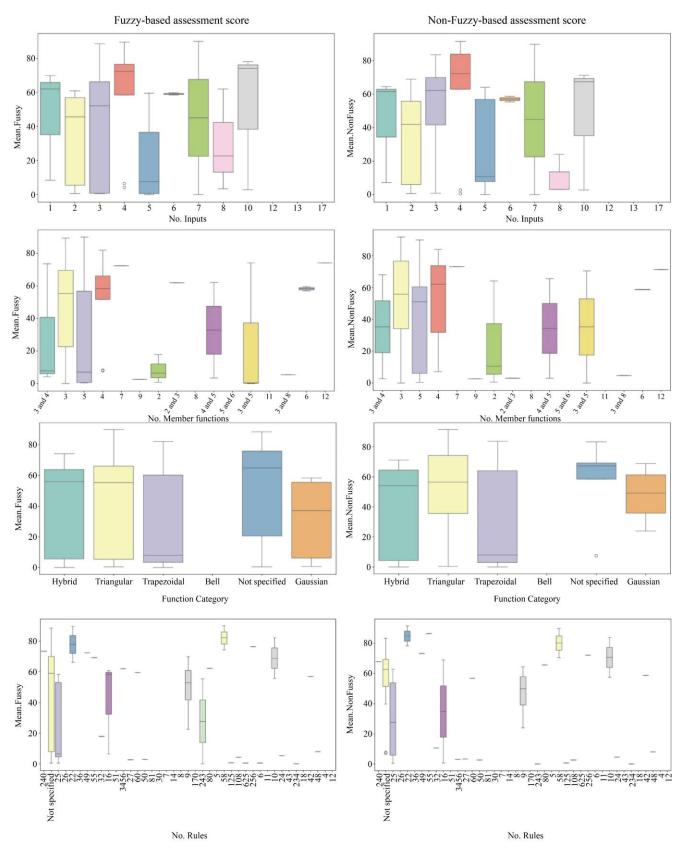
In terms of the output, combining two variables (no. membership functions and function categories) and three variables (no. outputs, no. membership functions, and function categories) showed high heterogeneity (P = 76%, p < 0.01), with frequency-based combinations again producing higher effect sizes (Hedges' g = 0.23 and Hedges' g = 0.27, respectively) (Figure 3).

• RQ6: What is the overall impact of fuzzy logic on student performance based on meta-analysis?

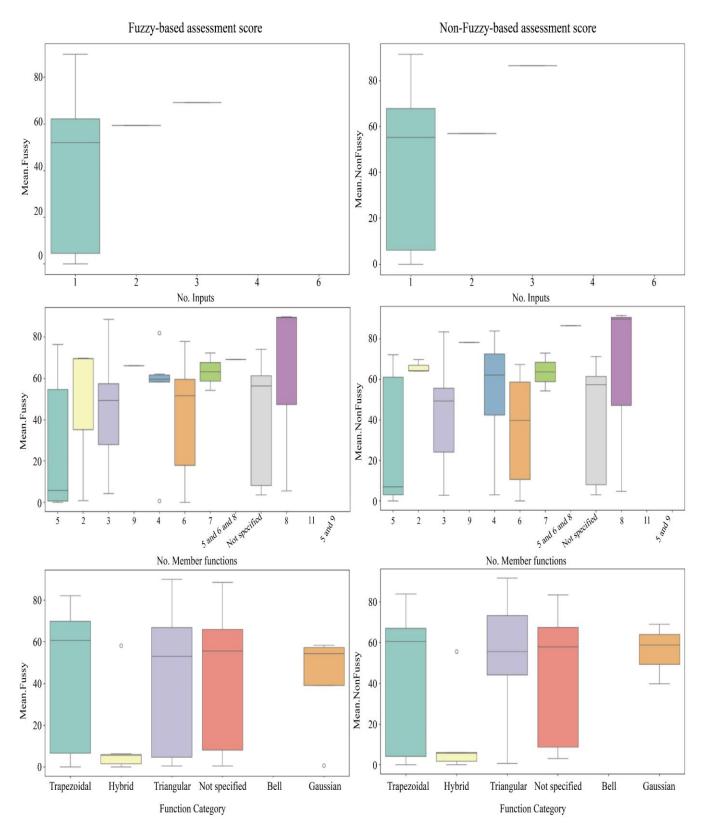
The meta-analysis revealed a small but positive overall effect size (Hedges' g=0.17), with significant heterogeneity (P = 78%). This suggests that while fuzzy logic provides performance benefits, results vary based on configuration.

 RQ7: Which configurations (input/output variables, membership functions, and rule types) yield the most consistent and effective outcomes?

Frequency-based configurations (i.e., those occurring in >10% of studies) delivered more consistent and moderately positive results (Hedges' g=0.60, P=68%). Adding more variables (e.g., rules) increased heterogeneity but did not significantly boost outcomes. In output analysis, frequency-based configurations again yielded higher effect sizes (Hedges' g=0.23-0.27).



(a) The input: Assessment scores based on fuzzy and non-fuzzy methods for each individual variable



(b)The output: Assessment scores based on fuzzy and non-fuzzy methods for each individual variable Fig. 2 Assessment scores and variables for choosing publications

Input: Combination of No. Inputs, No. Membership functions, Function Category

1		Fuz	zy logic	N	n_Fu	zy logic	Standardised Mean			
Study	Total	Mean			Mean	SD	Difference	SMD	95%-CI	Weight
Input_3Combination = No.Input	s (Fred	) + No.	Member	functi	ons (N	on-frea)	+ Function Category (Freg)			
Elfakki et al., 2023			11.3500			15.4600		0.40	[-0.24; 1.05]	2.8%
Gupta et al., 2022	10	72.35	9.9900	10	73.10	8.6600	+		[-0.95; 0.80]	2.3%
Tang et al., 2021	10	6.42	3.1300	10	0.63	0.2500	-	2.50	[ 1.27; 3.72]	1.6%
Parfenov and Zaporozhko, 2020			10.3800			10.1800			[-1.54; 0.96]	1.6%
Wardoyo and Yuniarti, 2020			11.9000			11.2000	₹_		[-0.30; 0.95]	2.9%
Krouska et al., 2019			0.8507			1.4903	<u>_</u>		[ 0.57; 1.94]	2.7%
Pooja et al., 2016			2.4900		4.66	2.0800	₹		[-0.47; 1.08]	2.5%
Random effects model Heterogeneity: $I^2 = 68\%$ , $\tau = 0.6592$ ,	97		0.01)	97			<b>S</b>	0.60	[ 0.01; 1.18]	16.4%
Heterogeneity: 7 = 66%, t = 0.6592,	χ <sub>6</sub> = 10	49 (p <	0.01)							
Input_3Combination = No.Input	s (Freq	) + No.	Member	functi	ons (Fi	req) + Fu	nction Category (Freq)			
Yoliadi, 2023	20	69.65	13.3100	20	69.65	13.3100	<b>+</b>	0.00	[-0.62; 0.62]	2.9%
Bisht et al., 2022			15.3200			8.4800			[-2.03; 0.21]	1.8%
Gogoi and Borah, 2022			28.8800			42.3600			[-1.35; 0.43]	2.2%
Wen and Liu, 2021			12.7500			12.6300	_		[-0.88; 0.87]	2.3%
Deb et al., 2019			25.6400			21.6200	1		[-0.50; 0.81]	2.8%
Mohamed et al., 2018			11.3500			6.3400 0.8800			[-0.16; 1.06]	2.9% 3.0%
Hajder and Micic, 2018 Darwish, 2017			0.1600			0.1600			[-1.20; -0.08] [-0.68; 0.56]	2.9%
Barlybayev et al., 2016			10.4500			9.1000	-		[-0.95; 0.59]	2.5%
Kharola et al., 2015			12.0800			14.5700			[-1.56; 0.95]	1.6%
Yadav et al., 2014			22.3400			20.6000			[-0.51; 0.73]	2.9%
Seyyed et al., 2013			21.8500			21.5800			[-0.64; 0.59]	2.9%
Gokmen et al., 2010			21.5600			20.6000	_		[-0.54; 0.70]	2.9%
Sripan and Suksawat, 2010			11.6100			9.4500			[-1.10; 0.01]	3.1%
Nshimyumuremyip et al., 2016	20	55.62	15.1700			13.2200			[-0.74; 0.50]	2.9%
Daniel et al., 2023	22	7.87	1.3300	22	7.98	1.6900		-0.07	[-0.66; 0.52]	3.0%
Loan et al., 2024	318	89.50	7.6900	318		7.1500		-0.27	[-0.43; -0.11]	3.9%
Chaudhari et al., 2023	21	0.54	0.2300	21	0.54	0.2100	e e	0.00	[-0.60; 0.60]	2.9%
Random effects model	617			617			4	-0.17	[-0.30; -0.04]	49.2%
Heterogeneity: $I^2 = 0\%$ , $\tau = 0.0778$ , $\gamma$	$\zeta_{17} = 15.$	44 (p =	0.56)							
Input_3Combination = No.Input	s (Non-	-freq) -	No.Men	nber fu	unction	s (Freq)	+ Function Category (Freq)			
Dam et al., 2022		The second second	21.1400			16.5000	#	0.15	[-0.73; 1.03]	2.3%
Konstantina et al., 2022	70	8.31	1.5900	70	7.15	1.5900			[ 0.38; 1.07]	3.6%
Lasunon, 2019	3	61.96	2.1500	3	61.46	2.0800	-	0.19	[-1.42; 1.80]	1.1%
Eryilmaz and Adabashi, 2020			22.8100			26.2560	<del>-</del>		[-0.41; 0.84]	2.9%
Azimjonov et al., 2016			5.4600		89.74	4.8800	<b>=</b>		[-0.60; 0.67]	2.8%
Random effects model	122		071	122			•	0.36	[-0.00; 0.73]	12.7%
Heterogeneity: $I^2 = 23\%$ , $\tau = 0.2481$ ,	$\chi_4 = 5.1$	9(p=0)	1.27)							
Input_3Combination = No.Input	s (Non-	-freq) +	No.Men	nber fu	unction	s (Non-	freg) + Function Category (F	reg)		
Arellano et al., 2022			1.4600			4.9300			[1.20; 2.74]	2.5%
Kurniawan and Utama, 2021	10	62.03	10.3600	10	3.04	0.3900	-		[4.92; 10.50]	0.5%
Salam et al., 2018	10	2.73	0.5900	10	2.73	0.5900	+	0.00	[-0.88; 0.88]	2.3%
Petra and Aziz, 2021			0.3500			0.3900	-		[ 0.39; 1.72]	2.8%
Meenakshi and Manisharma, 201			0.1000			13.5600	— <b>—</b> _		[-9.47; -2.44]	0.3%
			10.6700		71.20	10.7800	<u>+</u>		[-0.62; 1.14]	2.3%
Random effects model Heterogeneity: $I^2 = 90\%$ , $\tau = 3.8531$ ,	75		0.01)	75				0.91	[-2.27; 4.08]	10.6%
Heterogeneity: $I = 90\%$ , $\tau = 3.8531$ ,	$\chi_5 = 51$	.04 (p <	0.01)							
Input_3Combination = No.Input	s (Fred	) + No.	Member	functi	ons (F	reg) + Fu	nction Category (Non-freg)			
Namli and Senkal, 2018			21.9000					0.61	[ 0.38; 0.84]	3.8%
Namli and Senkal, 2016			15.2300			17.8800	-		[-1.67; 0.49]	1.9%
Random effects model	157			157			<b>*</b>	0.13	[-1.02; 1.28]	5.6%
Heterogeneity: $I^2 = 78\%$ , $\tau = 0.7509$ ,	$\chi_1^2 = 4.5$	6(p=0)	.03)						-	
Input 2Combination - No Issue	e (Non	frank	No Ma-	abor f	unetla-	e (Eres)	+ Function Catherny (No. )	rom\		
Input_3Combination = No.Input									[ 1.02: 0.00]	2.00/
Kumari et al., 2017	20	22.04	3.7200	20	24.00	2.8600	7	-0.40	[-1.03; 0.22]	2.9%
Input_3Combination = No.Input	s (Fred	) + No.	Member	functi	ons (N	on-frea)	+ Function Category (Non-	reg)		
Kai and Chee, 2011			18.4600			16.5200			[-0.82; 0.61]	2.6%
	,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,									AND THE PERSON OF THE PERSON O
Random effects model	្ន1103			1103				_ 0.17	[-0.03; 0.37]	100.0%
Heterogeneity: $I^2 = 78\%$ , $\tau = 0.5153$ , Test for subgroup differences: $\chi_6^2 = 14$	$\chi_{39}^2 = 17$	76.30 (p	< 0.01)					1		
Test for subgroup differences: $\chi_6^2 = 14$	4.00, df	= 6 (p =	0.03)			-	-10 -5 0 5	10		
							Standardized Mean Difference	ce		

(a) Combined 3 variables of the input

Input: Combination of No. Inputs, No. Membership functions, Function Category, No. Rules

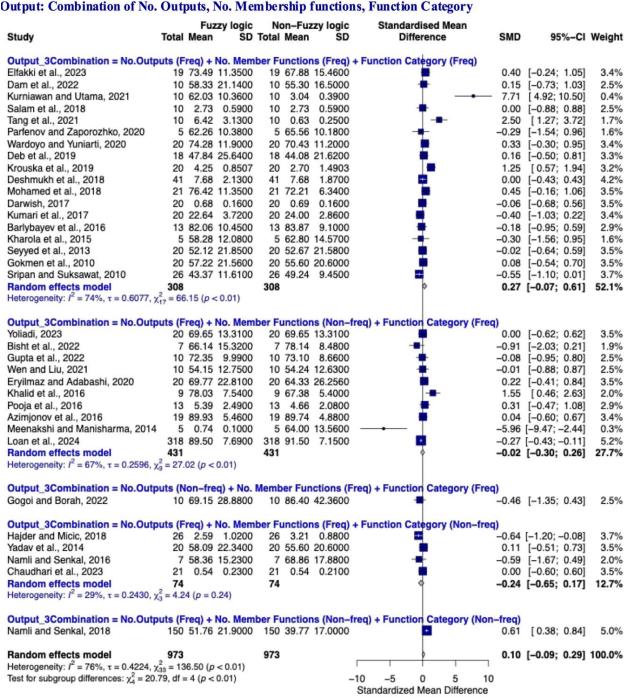
Study	Fuzzy log Total Mean S	ic Non–Fuzzy logic D Total Mean SD		D 95%-CI Weight
Input_4Combination = No.Inp Elfakki et al., 2023	outs (Freq) + No.Men 19 73.49 11.350		eq) + Function Category (Freq) + No	Rules (Non-freq) 0 [-0.24; 1.05] 3.4%
Gupta et al., 2022	10 72.35 9.990			8 [-0.95; 0.80] 2.7%
Tang et al., 2021	10 6.42 3.130			0 [1.27; 3.72] 2.0%
Parfenov and Zaporozhko, 2020				9 [-1.54; 0.96] 2.0%
Wardoyo and Yuniarti, 2020	20 74.28 11.900	00 20 70.43 11.2000	_	3 [-0.30; 0.95] 3.4%
Krouska et al., 2019	20 4.25 0.850	7 20 2.70 1.4903	<u>→</u> 1.2	5 [0.57; 1.94] 3.2%
Pooja et al., 2016	13 5.39 2.490			1 [-0.47; 1.08] 3.0%
Random effects model Heterogeneity: $I^2 = 68\%$ , $\tau = 0.659$	97 92, $\chi_6^2 = 18.49 (p < 0.01)$	97	♦ 0.6	0 [0.01; 1.18] 19.7%
			Function Category (Freq) + No.Rule	s (Non-fred)
Bisht et al., 2022	7 66.14 15.320			1 [-2.03; 0.21] 2.2%
Gogoi and Borah, 2022	10 69.15 28.880			6 [-1.35; 0.43] 2.7%
Mohamed et al., 2018	21 76.42 11.350		1	5 [-0.16; 1.06] 3.4%
Hajder and Micic, 2018	26 2.59 1.020	00 26 3.21 0.8800		4 [-1.20; -0.08] 3.6%
Darwish, 2017	20 0.68 0.160	00 20 0.69 0.1600	-0.0	6 [-0.68; 0.56] 3.4%
Barlybayev et al., 2016	13 82.06 10.450	00 13 83.87 9.1000	<del>-0</del> .1	8 [-0.95; 0.59] 3.0%
Nshimyumuremyip et al., 2016	20 55.62 15.170			2 [-0.74; 0.50] 3.4%
Daniel et al., 2023	22 7.87 1.330		The state of the s	7 [-0.66; 0.52] 3.5%
Loan et al., 2024	318 89.50 7.690			7 [-0.43; -0.11] 4.4%
Random effects model Heterogeneity: $I^2 = 15\%$ , $\tau = 0.000$	457 07. $\chi^2 = 9.36 (p = 0.31)$	457	<b>∮</b> −0.2	4 [-0.37; -0.11] 29.7%
			- () · 5 (5)	No Polos (Non feet)
			on-freq) + Function Category (Freq)	
Arellano et al., 2022 Kurniawan and Utama, 2021	20 17.88 1.460			7 [1.20; 2.74] 3.0% 1 [4.92; 10.50] 0.6%
Salam et al., 2018	10 62.03 10.360 10 2.73 0.590			1 [4.92; 10.50] 0.6% 0 [-0.88; 0.88] 2.7%
Random effects model	40	40		5 [-1.31; 7.41] 6.4%
Heterogeneity: $I^2 = 94\%$ , $\tau = 3.756$			3.0	5 [-1.51, 7.41] 6.476
	eran garanteen eran eran eran eran eran eran eran e			
	, ,,		Function Category (Freq) + No.Rule	
Wen and Liu, 2021	10 54.15 12.750			1 [-0.88; 0.87] 2.7%
Deb et al., 2019 Kharola et al., 2015	18 47.84 25.640 5 58.28 12.080			6 [-0.50; 0.81] 3.3% 0 [-1.56; 0.95] 2.0%
Yadav et al., 2014	20 58.09 22.340			1 [-0.51; 0.73] 3.4%
Seyyed et al., 2013	20 52.12 21.850			2 [-0.64; 0.59] 3.4%
Gokmen et al., 2010	20 57.22 21.560			8 [-0.54; 0.70] 3.4%
Sripan and Suksawat, 2010	26 43.37 11.610			5 [-1.10; 0.01] 3.6%
Chaudhari et al., 2023	21 0.54 0.230	0 21 0.54 0.2100		0 [-0.60; 0.60] 3.5%
Random effects model	140	140		7 [-0.30; 0.17] 25.3%
Heterogeneity: $I^2 = 0\%$ , $\tau = 0$ , $\chi_7^2 = 0$	4.06 (p = 0.77)			
			n-freq) + Function Category (Freq)	
Petra and Aziz, 2021	20 3.45 0.350	00 20 3.05 0.3900	<u>■</u> 1.0	6 [0.39; 1.72] 3.3%
Input 4Combination = No.Inc	outs (Non-freg) + No	Member functions (Fro	eq) + Function Category (Freq) + No	Rules (Freg)
Eryilmaz and Adabashi, 2020	20 69.77 22.810			2 [-0.41; 0.84] 3.4%
land (Cambination - No land	usta (Nam. Sana) - Na	Mambas from Name (For		No Dules (Free)
Kumari et al., 2017	20 22.64 3.720		eq) + Function Category (Non-freq)	0 [-1.03; 0.22] 3.4%
Input_4Combination = No.Inp Azimionov et al., 2016	outs (Non-freq) + No 19 89.93 5.460		eq) + Function Category (Freq) + No	Rules (Non-freq) 4 [-0.60; 0.67] 3.4%
Azimjonov et al., 2010	15 05.55 5.400	00 15 05.74 4.0000	T 0.0	4 [-0.00, 0.07] 3.476
			eq) + Function Category (Non-freq)	
Kai and Chee, 2011	15 56.93 18.460	00 15 58.80 16.5200	-0.1	0 [-0.82; 0.61] 3.2%
Input_4Combination = No.Inp	uts (Freq) + No.Men	nber functions (Freq) +	Function Category (Non-freq) + No	Rules (Non-freq)
Namli and Senkal, 2016	7 58.36 15.230	The state of the s		9 [-1.67; 0.49] 2.3%
Random effects model	835	835	0.1	5 [-0.08; 0.39] 100.0%
Heterogeneity: $I^2 = 75\%$ , $\tau = 0.558$				- ,,, 100.070
Test for subgroup differences: $\chi_9^2$ =	26.17, df = 9 (p < 0.01	)	-10 -5 0 5 10	
	•		Standardized Mean Difference	

(b) Combined 4 variables of the input

# Output: Combination of No. Membership functions, Function Category

	50 15 89		zzy logic			zzy logic		lardised Me	an		(C202220)	
Study	Total	Mean	SD	Total	Mean	SD		Difference		SMD	95%-	CI Weight
								í				
Output_2Combination = No. Mer			7				(Freq)					
Elfakki et al., 2023			11.3500			15.4600					[-0.24; 1.0	
Dam et al., 2022			21.1400			16.5000		•			[-0.73; 1.0	
Gogoi and Borah, 2022			28.8800			42.3600		•			[-1.35; 0.4	
Kurniawan and Utama, 2021			10.3600			0.3900		Ι,	-		[ 4.92; 10.5	
Salam et al., 2018			0.5900	10		0.5900		*		0.00	[-0.88; 0.8	
Tang et al., 2021			3.1300			0.2500		-			[ 1.27; 3.7	
Parfenov and Zaporozhko, 2020	5	62.26	10.3800	5	65.56	10.1800		-			[-1.54; 0.9	
Wardoyo and Yuniarti, 2020	20	74.28	11.9000	20	70.43	11.2000					[-0.30; 0.9	
Deb et al., 2019	18	47.84	25.6400	18	44.08	21.6200				0.16	[-0.50; 0.8	
Krouska et al., 2019	20	4.25	0.8507	20	2.70	1.4903		-		1.25	[ 0.57; 1.9	4] 3.2%
Deshmukh et al., 2018	41	7.68	2.1300	41	7.68	1.8700				0.00	[-0.43; 0.4	3] 4.2%
Mohamed et al., 2018	21	76.42	11.3500	21	72.21	6.3400		<b>=</b>		0.45	[-0.16; 1.0	6] 3.5%
Darwish, 2017	20	0.68	0.1600	20	0.69	0.1600				-0.06	[-0.68; 0.5	6] 3.5%
Kumari et al., 2017	20	22.64	3.7200	20	24.00	2.8600					[-1.03; 0.2	
Barlybayev et al., 2016			10.4500			9.1000					[-0.95; 0.5	
Kharola et al., 2015			12.0800			14.5700		-			[-1.56; 0.9	
Seyyed et al., 2013			21.8500			21.5800					[-0.64; 0.5	
Gokmen et al., 2010			21.5600			20.6000		<b>=</b>			[-0.54; 0.7	
Sripan and Suksawat, 2010			11.6100			9.4500		-			[-1.10; 0.0	
Random effects model	318		11.0100	318		5.4500					[-0.09; 0.5	
Heterogeneity: $I^2 = 73\%$ , $\tau = 0.5817$ ,			-0.01)	010				ľ		0.20	[-0.00, 0.0	0] 04.070
Treterogenery. 7 = 70%, t = 0.3017,	118 - 07	.04 (p ·	. 0.01)									
Output_2Combination = No. Mer	nhor E	unctio	ne (Non-	from)	. Euro	tion Cate	agent (Erea	VII				
Yoliadi, 2023			13.3100			13.3100	-			0.00	[-0.62; 0.6	2] 3.5%
Bisht et al., 2022			15.3200			8.4800					[-2.03; 0.2	
Gupta et al., 2022			9.9900			8.6600		I			[-0.95; 0.8	
Wen and Liu, 2021			12.7500			12.6300		<b>T</b>			[-0.88; 0.8	
Eryilmaz and Adabashi, 2020			22.8100			26.2560		<b>T</b>			[-0.41; 0.8	
Khalid et al., 2016			7.5400			5.4000		-			[ 0.46; 2.6	
Pooja et al., 2016			2.4900			2.0800					[-0.47; 1.0	
Azimjonov et al., 2016			5.4600			4.8800		•			[-0.60; 0.6	
Meenakshi and Manisharma, 2014			0.1000			13.5600	-				[-9.47; -2.4	
Loan et al., 2024		89.50	7.6900		91.50	7.1500					[-0.43; -0.1	
Random effects model	431			431				•		-0.02	[-0.30; 0.2	6] 27.7%
Heterogeneity: $I^2 = 67\%$ , $\tau = 0.2596$ ,	$\chi_9^2 = 27.$	02 (p <	0.01)									
Output_2Combination = No. Mer				+ Fur			(Non-freq)					
Hajder and Micic, 2018	26	2.59	1.0200	26		0.8800					[-1.20; -0.0	
Yadav et al., 2014	20	58.09	22.3400			20.6000				0.11	[-0.51; 0.7	3] 3.5%
Namli and Senkal, 2016	7	58.36	15.2300	7	68.86	17.8800		-		-0.59	[-1.67; 0.4	9] 2.0%
Chaudhari et al., 2023	21	0.54	0.2300	21	0.54	0.2100				0.00	[-0.60; 0.6	0] 3.5%
Random effects model	74			74				0		-0.24	[-0.65; 0.1	7] 12.7%
Heterogeneity: $I^2 = 29\%$ , $\tau = 0.2430$ ,	$\frac{2}{3} = 4.2$	4(p = 0)	).24)								•	•
	-		. (0.00)									
Output_2Combination = No. Mer	nber F	unctio	ns (Non-	freq)	+ Fund	tion Cate	gory (Non-	-freq)				
Namli and Senkal, 2018			21.9000					+		0.61	[ 0.38; 0.8	4] 5.0%
										etraJeli (	•	- Tital
Random effects model	973			973				b		0.10	[-0.09; 0.2	9] 100.0%
Heterogeneity: $I^2 = 76\%$ , $\tau = 0.4224$ ,		6.50 (p	< 0.01)									•
Test for subgroup differences: $\chi_3^2 = 18$							-10 -5	0 5	5 10			
λ3	, -	4						ed Mean Dif				

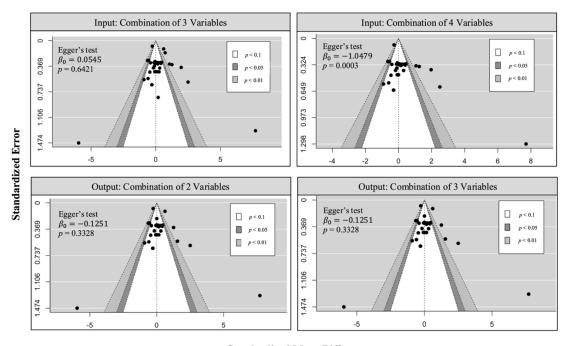
(c) Combined 2 variables of the output



(d) Combined 3 variables of the output
Fig. 3 Forest plots of combined variables with subgroups (the input and output)

Among the articles in this meta-analysis, the publication bias analysis was revealed. The contour-enhanced funnel plots for each article showed uneven scatter distributions, with points deviating from the pooled effect size represented by the vertical line. These observations are further supported by the results of Egger's regression tests. Specifically, the meta-analyses for input combinations of three and four variables

and output combinations of two and three variables showed that the intercept  $(\beta_0)$  significantly differed from zero, indicating the presence of publication bias (all  $\beta_0$  either  $\leq$  -0.1251 or  $\geq$  0.0545). Figure 4 illustrates the contourenhanced funnel plots, highlighting the asymmetry among the selected studies and corroborating Egger's regression findings.



Standardized Mean Difference

Fig. 4 The funnel plots highlight the asymmetries among studies (combination of various variables for the input and output)

#### 4. Discussion

The systematic review and meta-analysis of fuzzy and non-fuzzy logic approaches for assessing students' performance highlighted notable insights and implications for educational assessment practices. With a final selection of 109 studies for systematic review and 46 studies for meta-analysis, the findings underscored the increasing reliance on fuzzy logic methods in educational assessments, particularly for capturing nuanced student performance metrics. The significant number of articles analyzed provided a robust basis for comparing the effectiveness of fuzzy logic versus non-fuzzy methods, offering valuable insights into the optimal configurations for assessment variables. Of the 109 selected studies, the highest results in fuzzy and non-fuzzy-based assessment scores were achieved in the number of output member functions, with eight functions producing the highest median scores ( $\geq$  89.50).

The study's findings emphasized the significance of variables for the input and output in influencing assessment outcomes (e.g., the number of inputs, the number of membership functions, and the function categories). With ten inputs, 12 membership functions for the input, hybrid functions (triangular and trapezoidal) for the input, and trapezoidal functions for the output, fuzzy models got the highest results, demonstrating their ability to provide more complex categorizations and greater interpretive precision compared to non-fuzzy techniques, achieving scores of 74.10, 74.10, 56.12, and 60.72, respectively. These findings suggest that educators and administrators should prioritize developing future assessment models with appropriate output granularity to capture performance variations among students better.

Furthermore, the results correspond with findings from previous studies, which support their validity [125-128]. However, there were some variables that favored non-fuzzy-based assessments (e.g., no. outputs, no. rules, and no. membership functions). These findings highlight the strengths and limitations of both fuzzy and non-fuzzy approaches, emphasizing the contexts in which each method is best suited. While fuzzy-based assessments excel in handling complex, multi-dimensional, and nuanced data structures, non-fuzzy methods perform better in scenarios with fewer rules, outputs, and output membership functions [15, 85, 128].

The results of the meta-analysis (subgroup analysis) revealed that configurations of fuzzy logic systems play a critical role in the accuracy and reliability of student performance assessments. Frequency-based configurations, particularly when combining the number of inputs, the number of membership functions, and the function categories, consistently performed better than non-frequency counterparts. These results suggest that adopting a systematic approach to selecting frequency-based parameters can enhance the granularity and precision of fuzzy logic systems.

The introduction of additional variables, such as the number of rules, while increasing system complexity, did not consistently improve performance outcomes. This indicates that overcomplicated configurations may introduce diminishing returns and greater heterogeneity in study results. The substantial heterogeneity observed across all configurations (I $^2 \geq 68\%$ ) underscores the need for standardized reporting and parameter selection in future

research. While frequency-based combinations emerged as optimal in several cases, non-frequency-based setups occasionally produced outlier results, suggesting that specific contexts or educational settings may benefit from tailored configurations. These findings emphasize the importance of balancing system complexity and parameter selection to optimize fuzzy logic-based assessments. Future studies should further explore the interaction effects between variables and develop guidelines for best practices in designing fuzzy logic systems for educational goals [72, 129-132].

The significant heterogeneity observed across studies ( $I^2 \ge 75\%$ ) reflects not only methodological diversity but also the influence of specific fuzzy logic configurations. Subgroup analyses demonstrated that frequency-based configurations reduced variability and yielded more consistent outcomes, suggesting that careful selection of input and output parameters can mitigate heterogeneity. In contrast, non-frequency-based designs introduced higher inconsistency, highlighting the need for standardized approaches in future research.

These findings indicate that heterogeneity is not solely a limitation of the analysis but also a meaningful signal of how different configurations shape the reliability and effectiveness of fuzzy logic in educational assessment. This study had several limitations. Factors (e.g., educational contexts, sample sizes, and study designs), which could affect heterogeneity,

were not fully accounted for. A lack of full-text articles and incomplete information related to configurations among combined variables also affected the comprehensiveness of the meta-analysis. In future work, examining the differences among other factors (e.g., subjects, student demographics) influencing assessment outcomes will be the focus. In addition, refining subgroups based on contextual factors to improve fuzzy logic in educational assessments.

#### 5. Conclusion

This systematic review and meta-analysis illustrated the benefits of fuzzy logic in student performance assessments and provided guidance on optimal configurations for these systems. Key findings on variable importance and the value of variables of the input and output factors influenced assessment outcomes (e.g., the number of inputs, the number of membership functions, and the function categories), while subgroup differences highlight the potential for tailored configurations. Exploring context-specific configurations in education could improve fuzzy logic in assessment in future work.

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