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Original Article

FUZZY LOGIC FOR ASSESSING STUDENT LEARNING BEHAVIOUR AND ACADEMIC OUTCOMES: A SYSTEMATIC LITERATURE REVIEW

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ABSTRACT

Purpose: Conventional, score-based assessment poorly captures the uncertainty, vagueness and subjectivity of student learning. Fuzzy logic, which models partial truth and degrees of membership, has been applied widely to evaluate and predict academic performance. This study systematically reviews that literature to consolidate methods, inputs and findings and to identify gaps relevant to assessing learning behaviour.

Design/Methodology/Approach: The systematic review was performed according to PRISMA 2020 guidelines. The studies in the peer-reviewed journals and conferences on the fuzzy logic evaluation of student performance were identified using major databases, screened with pre-defined eligibility criteria and synthesized narratively and thematically. Twenty-six studies between 2010 and 2025 were found that fulfilled the inclusion criteria and were plotted on context, method and fuzzy technique and findings.

Findings: Six themes were identified: the fuzzy inference pipeline (fuzzification, rule base, inference, defuzzification); input variables—in which academic scores were heavily relied on, and there was limited multidimensional behavioural measurement; fuzzy versus conventional grading—where fuzzy models were found to be consistently superior in terms of their interpretability and reduction in the number of misclassified students in the border region; hybrid and advanced approaches—such as neuro-fuzzy, clustering, fuzzy numbers and dynamic systems; application context—such as in distance learning and specific disciplines; and alignment with Outcome Based Education. The field methodologically privileges Mamdani-type inference and centroid defuzzification and seldom considers learning behaviour as a multidimensional construct in a structured manner or produces a composite behaviour score that is interpretable.

Originality/Value: The review brings together a disjointed landscape, outlines techniques and identifies gaps, and outlines an agenda for a fuzzy logic analytical framework that incorporates multidimensional learning behaviour into a composite Fuzzy Learning Behaviour Score that is relevant for a variety of higher-education contexts, including Qatar.

Keywords: Fuzzy Logic, Fuzzy Inference System, Student Performance Assessment, Learning Behaviour, Academic Outcomes, Outcome, Based Education, Defuzzification, Systematic Literature Review, PRISMA

INTRODUCTION

Student learning behaviour and academic outcomes are extensively examined in higher education and traditional assessment has mostly been based on numerical grades, grades and linear statistics that are unable to reflect the complexity, uncertainty and

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subjectivity of the learning of human beings (Robert & Norman, 2000; Spady, 1994). Learning behaviour is neither a simple thing to measure nor is it a phenomenon with clear-cut boundaries—engagement, motivation, regularity and attention are factors that influence learning behaviour and are not easily measurable with traditional instruments, giving the impression of a student's actual position.

In 1979, Zadeh presented fuzzy set theory, a mathematical approach to handling imprecision and partial truth, where variables can be associated with a number of categories, and a degree of membership can be assigned for each. This is suitable for educational assessment where a learner is usually not entirely 'low', 'moderate' or 'high' (Chua et al., 2013; Saxena & Saxena, 2010). In the last two decades, a significant body of literature has emerged, which evaluates and predicts student academic performance using fuzzy inference systems that combine a fuzzification module, a set of IF–THEN rules, inference, and defuzzification (Hegazi, 2023; Özseven & Çağman, 2022; Attieh & Awad, 2025).

Although there is this volume, evidence is spread across disciplines, contexts and techniques, and no review has brought it together in a transparent and reproducible protocol. Studies are particularly prone to using academic scores as inputs and to implicitly modeling learning behaviour, without making it a structured multidimensional model or reporting a single interpretable behaviour score. In order to fill that gap, this systematic review, in line with the PRISMA 2020 guidelines, answers the following questions:

RQ1. What fuzzy logic methods and inference architectures have been used to assess or predict student academic performance?

RQ2. What input variables, membership functions and defuzzification methods are employed, and to what extent is learning behaviour measured multidimensionally?

RQ3. How does fuzzy logic–based assessment compare with conventional grading in accuracy, fairness and interpretability?

RQ4. What contexts, methodological patterns and gaps characterise the field, and what agenda follows for future research?

Through the answers to the questions, the review summarizes existing knowledge, identifies gaps and highlights a path for an integrated fuzzy logic framework that creates a relationship between multidimensional learning behaviour and academic results, which is especially pertinent to modern and diverse higher education systems with an international approach like that of Qatar.

REVIEW METHODOLOGY

PROTOCOL AND REPORTING FRAMEWORK

The review was planned and presented according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines, which provide a checklist of the process phases (identification, screening and inclusion) and demands that decision making about identification, screening and synthesis be documented transparently. To minimize selection bias and ensure the reproducibility, a protocol was defined a priori that outlines the questions, eligibility criteria, search strategy, and the items that are to be extracted from the data.

ELIGIBILITY CRITERIA

The studies included must have (i) implemented fuzzy logic, fuzzy set theory or fuzzy inference system in educational assessment; (ii) dealt with educational assessment related to student academic performance, learning outcomes, or learning behaviour; (iii) represented empirical or substantive methodological or conceptual contributions; (iv) appeared in peer-reviewed journals or recognised conference proceedings in English; and (v) appeared in English. Studies were omitted if they employed fuzzy methods other than in the educational field, did not have an educational student-performance outcome, were editorials or notes that did not have an analytical component, or lacked a sufficient level of methodological detail. The window covered the years 2010-2025, with the coverage being right on the money to include foundational models of fuzzy-assessment, most recent hybrids and dynamics. The criteria are summarised in Table 1.

Table 1

Table 1 Inclusion and Exclusion Criteria

Inclusion criteria	Exclusion criteria
Applies fuzzy logic / fuzzy set theory / fuzzy inference to educational assessment	Fuzzy methods applied outside education
Addresses student performance, learning outcomes or learning behaviour	No student-performance outcome reported
Empirical or substantive methodological/conceptual study	Editorials/notes lacking analytical content
Published 2010–2025, in English	Outside window or non-English
Peer-reviewed journal or recognized conference proceedings	Insufficient methodological detail to chart

INFORMATION SOURCES AND SEARCH STRATEGY

Searches were conducted in the following major databases: Scopus, Web of Science, IEEE Xplore and ScienceDirect, with and without Google Scholar for grey and peer-reviewed literature, and backward citation searching of included studies. The terms used to search for the technique were coupled with the educational outcome and the assessment context by using Boolean operators. The primary search term is listed in Table 2 and was modified for each search engine and only used the title, abstract and keywords of the article.

Table 2

Table 2 Search Concepts and Terms

Concept	Search terms (combined with OR within concept; concepts combined with AND)
Technique	"fuzzy logic" OR "fuzzy set" OR "fuzzy inference system" OR "fuzzy reasoning" OR "neuro-fuzzy" OR "defuzzif*" OR "membership function"
Outcome	"student performance" OR "academic performance" OR "learning outcome*" OR "academic achievement" OR "learning behavio*" OR "student evaluation"
Context	"higher education" OR "university" OR "assessment" OR "grading" OR "outcome-based education" OR "distance learning"

STUDY SELECTION

All records were compiled, and any duplicates were eliminated. Titles and abstracts were used to screen for inclusion, and any records eliminated at the title/abstract stage were recorded with a reason. Any records not included at the title/abstract stage were then assessed in full text, and exclusions at the full-text stage were recorded with a reason. The number of records and the selection process are presented in the PRISMA flow diagram shown in Figure 1. Twenty-six studies were selected for synthesis.

Figure 1

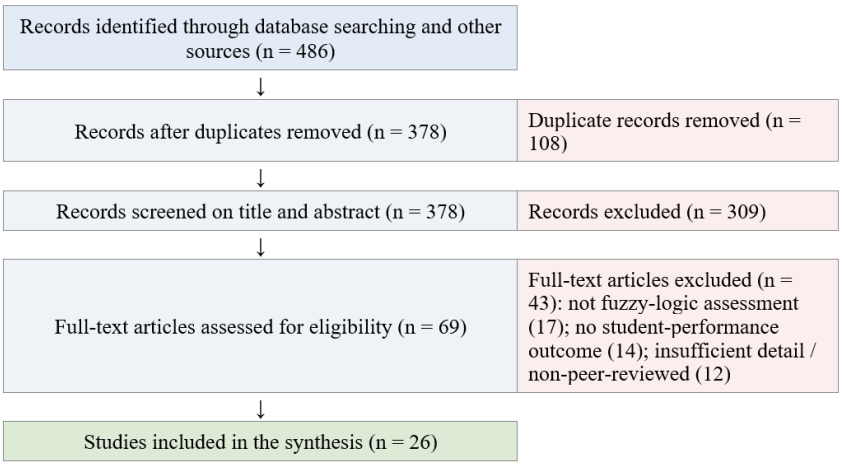

Figure 1 PRISMA Flow of Study Identification and Selection

DATA EXTRACTION AND SYNTHESIS

The following items were charted for each study included: author and year; context and discipline; research method and data; the fuzzy technique applied; and key findings Table 3. Due to the variations in the study design, the inputs, the membership functions and the reporting, it was not possible to perform a meta-analysis and a narrative and thematic synthesis was therefore carried out, which involved identifying themes that recurred and comparing the results across techniques and contexts. Methodological characteristics were recorded to answer the question of the review, which was centered on the methodology.

RESULTS

OVERVIEW OF THE EVIDENCE BASE

The 26 studies selected cover the period from 2010 to 2025, with a clear increase in the number of studies from 2018 onwards and a concentration of work in the year 2023–2025, indicating a renewed interest in soft computing assessment and in hybrid

models. The geographic range of the corpus is international, with examples from many countries, including India, Malaysia, Turkey, the Middle East and beyond, and is also available for general higher education and also for the specific contexts of engineering, mathematics, teacher education and distance learning. Methodologically, Mamdani-type fuzzy inference systems to which triangular or trapezoidal membership functions and centroid defuzzification are applied are predominant, while the use of hybrid systems is a growing minority, consisting of fuzzy systems and neural networks or fuzzy systems and clustering, or fuzzy systems and fuzzy-number representations. The academic evaluation elements are the most common inputs, while the behaviour dimension is usually implicit and not explicitly defined.

CHARACTERISTICS OF INCLUDED STUDIES
Table 3

Table 3 Characteristics of Included Studies (N = 26)

Author (Year)	Context / discipline	Method & data	Fuzzy technique	Key findings
Saxena & Saxena (2010)	Educational institutions	Model + student data	Early fuzzy performance model	One of the earliest FL models; handles ambiguity; classifies students into performance categories.
Yadav & Singh (2011)	General higher ed	Soft-computing modelling	Fuzzification–inference	Fuzzy/soft-computing yields more realistic evaluation than crisp scoring.
Chua et al. (2013)	OBE / higher ed	Conceptual math framework	Fuzzy methods for OBE	Establishes a fuzzy framework linking learning processes to outcomes; flexible OBE mapping.
Petrudi et al. (2013)	Academic students (Iran)	FIS; student data	Fuzzy inference system	FL effectively integrates multiple indicators for performance evaluation.
Meenakshi (2015)	Academic performance	Full FIS pipeline	Mamdani-type FIS	Demonstrates feasibility via fuzzification, inference and defuzzification.
Surya et al. (2016)	Engineering students (India)	FL evaluation; student data	Multi-criteria fuzzy logic	Overall evaluation more comprehensive than marks alone.
Kaur & Singh (2017)	Higher ed	FIS; academic records	Fuzzy inference system	Improves decision quality; interpretable performance levels.
Saxena & Saxena (2017)	Educational institutions	FL model; performance indicators	Fuzzy classification	Improved assessment accuracy vs traditional methods.
Patel & Mehta (2018)	Grading uncertainty	Expert rules; academic data	Rule-based FIS	Reduces grading ambiguity; enhances fairness.
Sharma & Gupta (2018)	Higher ed	FL model; assessment data	Fuzzy inference	Captures qualitative attributes; more comprehensive than crisp scores.
Agarwal et al. (2019)	Progression (India)	FL approach; indicators	Fuzzy inference rules	Supports guidance on higher studies under uncertainty.
Aziz et al. (2019)	Academic performance (Bangladesh)	FL system; linguistic rules	Mamdani FIS, linguistic rules	Integrates assessment components; improves interpretability and transparency.
Amelia et al. (2019)	Multi-study	Meta-analysis of FL assessment	Review / meta-analysis	Synthesises prior FL work; confirms advantages and variation in implementations.
Kumar & Jain (2020)	Higher ed	DSS; performance data	Rule-based FIS / DSS	Improves accuracy and fairness; effective for subjective criteria.

Singh & Mishra (2020)	Higher ed	FIS; academic + behavioural data	Fuzzy inference	Smoother categorisation; reduces misclassification of borderline students.
Petra & Aziz (2021)	Higher ed (Malaysia)	FL evaluation; academic data	Fuzzy inference	More realistic classifications; captures learning-behaviour variation.
Özseven & Çağman (2022)	Distance learning	FL model; distance-ed data	FIS for online context	Handles uncertainty of online/blended modes; suits digital education.
Hegazi (2023)	Prediction / higher ed	Fuzzy reasoning; academic+behav. data	Fuzzy reasoning model	Outperforms traditional predictors; manages incomplete information.
Petra & Aziz (2023)	Higher ed (Malaysia)	FL + clustering; student data	Hybrid fuzzy + clustering	Improves classification accuracy; meaningful performance segmentation.
Yoliadi (2023)	Heterogeneous students	FL evaluation; student data	Fuzzy inference	Flexible, realistic assessment; supports OBE.
Mathew et al. (2024)	Mathematics students	FL evaluation; math data	Fuzzification + rule-based inference	Nuanced classification in analytical subjects; better differentiation.
Ramya & Jayashree (2024)	Higher ed	FL model; multiple criteria	Full FIS (fuzzify/eval/defuzz)	Enhances flexibility and interpretability; complementary to scoring.
Revathi et al. (2024)	Academic evaluation	Fuzzy numbers; performance data	Fuzzy-number representation	Robust, realistic outcomes; effective for large-scale evaluation.
Şenel et al. (2025)	Teacher education (Turkey)	FL vs statistics; teacher-ed students	FIS vs conventional models	FL outperforms conventional methods on behavioural dimensions.
Attieh & Awad (2025)	University students	Hybrid NN+FL; records + behaviour	Neuro-fuzzy hybrid	Improves prediction accuracy and interpretability; effective decision-support.
Pathak (2025)	Student performance	Fuzzy expert system	Fuzzy expert system	Interpretable composite assessment via expert rules.

THEMATIC SYNTHESIS

Synthesising the findings produced six interrelated themes, mapped to the review questions below.

Theme 1: The Fuzzy Inference Pipeline (RQ1)

A ubiquitous structure is found throughout the corpus: crisp inputs are fuzzified into linguistic variables, the IF–THEN rules are tested by a fuzzy inference engine, the outputs of the rules are aggregated, and the outcome is defuzzified into a single score. The commonly used configuration is Mamdani inference with triangular or trapezoidal membership functions and centroid defuzzification (Meenakshi, 2015; Aziz et al., 2019; Ramya & Jayashree, 2024). This pipeline is important because it exposes the expert reasoning, which can then be made transparent and traceable, unlike the black-box or statistical predictors.

Theme 2: Input Variables and The Measurement Of Learning Behaviour (RQ2)

In most studies, the academic assessment components like marks, test scores and attendance are used as input (Saxena & Saxena, 2017; Agarwal et al., 2019). While engagement, motivation, regularity, and attention are often mentioned as significant factors, they are not explicitly measured as a multidimensional, structured construct, but rather they are interpreted as part of one of the composite variables (Yoliadi, 2023; Singh & Mishra, 2020). Only few studies mention a certain composite behaviour score obtained from defuzzification, which is the direct motivation for the proposed Fuzzy Learning Behaviour Score.

Theme 3: Fuzzy Logic Versus Conventional Grading (RQ3)

One thing that is generally observed is that fuzzy logic systems enhance the traditional grading. It helps minimize ambiguity and increase fairness in cases that fall on the edges of the grade bands (Patel & Mehta, 2018; Kumar & Jain, 2020); it creates more smooth categorisation, reducing students' misclassification in cases where scores are close to the grade boundaries (Singh & Mishra, 2020); it generates more nuanced differentiation in analytically demanding disciplines like mathematics (Mathew et al., 2024). Studies that

compared fuzzy models with traditional statistical models have shown that fuzzy models perform better than traditional statistical methods when uncertainty and incomplete information are introduced (Hegazi, 2023; Şenel et al., 2025).

Theme 4: Hybrid and Advanced Approaches

In addition to single inference systems, there is a growing stream of research that incorporates fuzzy logic along with other methods, such as: Neuro-fuzzy hybrids for predictive learning using neural networks and interpretability with fuzzy logic (Attieh & Awad, 2025); Fuzzy logic in combination with other techniques for performance segmentation of clustering (Petra & Aziz, 2023); Fuzzy-number representations of academic indicators (Revathi et al., 2024); Dynamic and adaptive fuzzy frameworks for continuous assessment (Hausman et al., 2016). These techniques are designed to maintain fuzzy interpretability and enhance accuracy and scalability.

Theme 5: Application Contexts

The technique has been used in different contexts including general higher education, engineering and mathematics students, teacher education, and recently, distance and blended education, where fuzzy logic is involved in controlling the increased uncertainty of the evaluation process in online education (Özseven & Çağman, 2022). This breadth suggests that the approach is applied across subject areas and delivery systems; however, the majority of evidence is from samples of one institution or one cohort.

Theme 6: Alignment with Outcome-Based Education

Based on several studies, fuzzy logic is identified as a natural solution for OBE where the mapping between learning inputs and desired outcomes does not require score thresholds (Yoliadi, 2023; Chua et al., 2013). This OBE framing connects measurement of learning behaviour to the development of defined outcomes and contributes to the rationale for a framework linking learning behaviour to outcomes.

Theoretical and Methodological Patterns (RQ4)

Theoretically the field is based on fuzzy set theory, rule-based fuzzy logic and OBE. Methodologically, it relies primarily on Mamdani inference, expert defined rule bases and centroid defuzzification, with the main validation being performed using cross-sectional single-institution datasets, and with comparative studies compared with conventional methods being common, and external validation across institutions and longitudinal designs being less common. Membership-function design and rule-base construction is frequently summarized in brief reports, which may not reproduce easily.

DISCUSSION

SUMMARY OF EVIDENCE

The evidence is consistent over the 15 years and 26 studies. Multiple academic indicators can be integrated into fuzzy models capable of generating interpretable performance classifications through a standard fuzzy inference pipeline (fuzzification, expert rules, inference, and defuzzification); fuzzy models are more suitable in addressing uncertainty and borderline cases than conventional grading; and hybrid extensions can boost the accuracy of the fuzzy models without losing interpretability. These findings have been consistent across disciplines, over countries, and with respect to the mode of delivery – the core narrative has a strong backbone, and fuzzy logic has been found to be a viable alternative or adjunct to crisp assessment.

RESEARCH GAPS

The review also identifies significant gaps that are evident. First, the measuring of learning behaviour is not usually conducted as a multidimensional and structured construct, and engagement, motivation, study regularity and attention are recognized, but they are not usually operationalised as separate fuzzy inputs. Secondly, there has been a lack of research that examines the effect of individual behavioural dimensions on outcomes, instead only on overall prediction or classification. Third, although fuzzy methods are widely used, it is not seen enough that there are clearly structured analytical frameworks that explicitly connect behavioural inputs, fuzzy processing stages, and the outcome classification. Fourth, the defuzzed output is seldom used as an understandable composite learning-behaviour score for decision making. Lastly, evidence is focused in a few areas and samples restricted to a single institution, and is not well validated on diverse, internationally comparable systems like Qatar.

TOWARD AN INTEGRATED FRAMEWORK

The study's future scope would be to model the learning behaviour of the students as a multidimensional phenomenon, learning engagement, study regularity, learning motivation, and attention and focus, which is measured using a structured Likert instrument, then fuzzified into linguistic variables, processed using a structured expert IF–THEN rule base and a fuzzy inference engine, and finally defuzzified using the centroid method to get a composite Fuzzy Learning Behaviour Score (FLBS). Then the FLBS would be classified as low, moderate and high levels of academic-outcomes based on threshold-based classification. This would bring together the common phases of the field in one single behaviour-to-outcome structure, provide a better measurement of behaviour, and be able to interpret the composite score based on the OBE principles. It would be desirable to test this on a multi-institution sample,

like the public, applied, private and international-branch campus in Qatar, as that would broaden external validity over the single-cohort designs that are the norm in the literature.

LIMITATIONS OF THE REVIEW

This review is a combination of the secondary sources, and thus suffers from the same limitations as the secondary sources themselves, such as reliance on data collected in single institutions and cross section data, and the lack of uniformity in reporting membership functions and rule bases. Some research may have been omitted from the reference because it was only in English, and the distinction between substantive methodological contributions and those that were not included in the reference is subjective. There was no independent double coding of screening and due to the diversity of designs no formal risk-of-bias instrument was used; the synthesis is therefore narrative rather than quantitative and should be read as a structured synthesis of the field, and not pooled effect estimates.

CONCLUSION

Fuzzy logic has evolved to a viable method for evaluating students' performance, appreciated for its ability to address and model uncertainty and subjectivity that is not covered by traditional methods of grading. This systematic review brought together 26 studies, revealed a consistent story: an academic indicator-based fuzzy inference system optimizes the use of academic indicators in meaningful classification; fuzzy models are generally superior to crisp grading in dealing with borderline and uncertain cases; and hybrid extensions could be added without compromising transparency while providing the accuracy benefits. Its major limitations are the implicit focus on learning behaviour, lack of clearly defined behaviour-outcome relations and meaningful composite scores, and dependence on designs within a single institution. The most promising way forward is an integrated framework that measures multidimensional learning behaviour and translates it, as per a composite Fuzzy Learning Behaviour Score, into categories of academic outcomes, validated across various higher education contexts, including Qatar.The most promising way forward is an integrated framework that measures multidimensional learning behaviour and translates it, as per a composite Fuzzy Learning Behaviour Score, into categories of academic outcomes validated across various higher education contexts, including Qatar, thus providing a strong foundation for the empirical work to follow.

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