A Theoretical AI - Fuzzy Logic Framework for Student Learning Profiles and Differentiated Instruction in Primary Education

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Received: January 5, 2026. Revised: April 24, 2026. Accepted: May 22, 2026. Published: August 3, 2026.

Abstract: - **This theoretical paper presents an AI-supported fuzzy logic framework for classroom grouping and individualized instruction in primary education. The learner profile integrates three dimensions elicited via a chatbot using a three-point scale: VARK, learning preferences, and interests. Student responses are mapped to fuzzy membership values to construct a compact learner vector enabling dynamic, non-rigid classification. A Mamdani inference mechanism aggregates IF–THEN rules to generate graded recommendations across five pedagogical approaches: Project-Based Learning, Challenge-Based Learning, STEAM, Makerspace/Experiential–Collaborative Learning, and Game-Based Learning. Based on these recommendations, a grouping module supports the formation of heterogeneous or homogeneous student teams aligned with instructional goals. A simulation across varying class sizes indicates that the framework maintains low grouping time while preserving higher group-quality indicators compared to random and manual grouping strategies. The main contributions include a lightweight learner-profile model, fuzzy pedagogical recommendations, and a flexible grouping workflow complementing teacher judgment.**

Keywords: - chatbot, grouping, profiles, fuzzy logic, differentiation, primary education

I. INTRODUCTION

The increasing recognition that learning is highly individualized and context-dependent has intensified interest in personalized and adaptive learning systems in primary education. Approaches that support differentiated instruction aim to accommodate learner diversity in terms of interests, preferences, and learning characteristics, while remaining feasible within everyday classroom constraints. In this context, educational technologies that integrate learner modeling and artificial intelligence offer promising opportunities for supporting instructional decision-making in a systematic and scalable manner, [1], [2], [3].

Our previous research has focused on the use of cutting-edge technologies, like augmented reality and three-dimensional technologies, to support innovative and engaging learning experiences in elementary education, [4], [5]. The current study advances this line of inquiry toward data-informed instructional decision-making in primary education by focusing on AI-supported learner profiling and differentiated instructional decision support.

Despite this growing interest, most adaptive learning systems have been developed for secondary or higher education settings, where learners are generally capable of self-reporting complex constructs such as motivation, self-regulation, or metacognitive strategies. In primary education, however, the design of adaptive systems faces distinct challenges. Learner modeling tools must be pedagogically valid, age-appropriate, and cognitively accessible, while avoiding excessive complexity that could limit their practical adoption by teachers, [6].

This paper proposes a fuzzy-logic–based framework that maps key learning characteristics of primary school students to recommended teaching approaches and classroom grouping strategies. Learner profiles are constructed through structured chatbot interactions and are treated as flexible, multidimensional representations rather than fixed categories. By allowing partial memberships across learning styles, learning preferences, and interests, the proposed approach captures the inherent uncertainty and variability of young learners' characteristics.

The framework is designed to support, rather than replace, teacher judgment. Its purpose is to provide data-informed guidance that can assist teachers in forming pedagogically meaningful instructional groups and adapting them over time as learner profiles evolve. Group formation is therefore viewed as a dynamic process aligned with instructional goals, rather than a static classification task.

The contribution of this work is threefold. First, it introduces an AI-enabled fuzzy-logic model that translates qualitative learner characteristics into quantitative vector representations suitable for adaptive decision support. Second, it demonstrates how these representations can inform pedagogical recommendations and classroom grouping decisions. Third, it presents a simulation-based analysis that examines the framework's behavior across different class sizes, focusing on grouping efficiency and group-quality trends.

It should be noted that the present study is fully simulation-based and does not involve real student data. Simulation is employed to explore feasibility, computational behavior, and design implications prior to empirical classroom implementation. Accordingly, the reported findings reflect algorithmic performance rather than direct pedagogical outcomes.

The remainder of the paper is organized as follows. Section 2 formulates the problem and outlines the learner-profile representation, Section 3 describes the proposed fuzzy-logic–based solution, Section 4 presents the simulation results, and Section 5 discusses implications for practice and future research.

II. PROBLEM FORMULATION

Classroom grouping constitutes a recurring and pedagogically significant challenge in primary education, particularly in learning environments that emphasize differentiation, collaboration, and learner-centered instruction. Teachers are often required to form student groups under time constraints and with limited access to structured learner data, leading to grouping decisions that rely on intuition, ad hoc criteria, or random assignment. As class size increases and learner diversity becomes more pronounced, the cognitive and organizational demands of group formation intensify, highlighting the need for systematic decision-support mechanisms.

In primary education, the formulation of such mechanisms is constrained by developmental and contextual factors. Unlike older students, young learners cannot reliably self-report complex constructs such as motivation, metacognition, or self-regulation, and are therefore ill-suited to conventional learner modeling approaches developed for secondary or higher education contexts. Effective learner profiling in primary classrooms must rely on pedagogically meaningful characteristics that can be elicited through age-appropriate, cognitively accessible interactions, while remaining feasible for everyday classroom use, [1], [2].

Within this context, learner profiles are conceptualized in this work as flexible, multidimensional representations rather than fixed categorical assignments. Building on perspectives that view learner characteristics as context-dependent and evolving, the proposed formulation focuses on three core dimensions: learning styles, learning preferences, and interests. These dimensions are directly relevant to instructional design and group composition and can be captured through simple learner–system interactions. Importantly, learners may partially exhibit multiple characteristics simultaneously, rendering rigid classification schemes inadequate for representing their profiles, [7].

The problem addressed in this study is therefore twofold. First, there is a need to construct learner representations that capture uncertainty, partial membership, and variability in young learners' characteristics without imposing excessive cognitive or methodological complexity. Second, these representations must be operationalized to support classroom grouping decisions that align with instructional goals, such as promoting diversity through heterogeneous grouping or similarity through homogeneous grouping. Addressing these interconnected challenges requires a modeling approach capable of translating qualitative learner information into actionable decision-support outputs, while remaining transparent and adaptable for teacher use.

A. Learner profile representation

To support systematic classroom grouping in primary education, the proposed framework adopts a learner profile representation that balances pedagogical relevance with practical feasibility. Rather than relying on extensive assessments or complex psychometric instruments, learner profiles are designed to capture a small set of core characteristics that can meaningfully inform instructional planning and group composition in everyday classroom contexts.

Consistent with principles of differentiated instruction, learner profiles focus on characteristics that reflect how students prefer to engage with learning activities and content. In this work, three dimensions are considered: learning styles, learning preferences, and interests. Learning styles describe preferred modes of information processing, learning preferences indicate tendencies toward individual, collaborative, or hands-on learning contexts, and interests capture thematic inclinations that influence student engagement. These dimensions are widely recognized as relevant for instructional design and differentiation and can be meaningfully addressed in primary education settings, [1], [3].

Importantly, learner characteristics are not treated as fixed or mutually exclusive categories. Young learners may simultaneously exhibit multiple preferences or interests, and these characteristics may evolve over time in response to instructional experiences and developmental factors. Accordingly, the learner profile is conceptualized as a multidimensional and flexible

DOI: 10.46300/9109.2026.20.17 Volume 20, 2026

representation that allows partial associations across multiple dimensions, rather than enforcing rigid classifications, [2], [5].

This representation serves as the conceptual foundation for the fuzzy modeling approach adopted in the proposed framework. By structuring learner information in a way that preserves uncertainty and variability, the learner profile can be operationalized for adaptive pedagogical recommendations and dynamic group formation. The following subsection describes how learner data are elicited through age-appropriate chatbot interactions and prepared for subsequent fuzzy inference.

A.1 Chatbot-based data collection

Learner information in the proposed framework is collected through structured chatbot interactions specifically designed for primary school students. The chatbot presents short, age-appropriate prompts related to learning styles, learning preferences, and interests, enabling learners to respond in an intuitive and low-effort manner. This approach avoids the cognitive and linguistic demands associated with traditional questionnaires and is better aligned with the developmental characteristics of young learners, [8], [9].

Student responses are elicited using a three-point scale that allows learners to indicate tendencies rather than precise self-assessments. The restricted response format reduces cognitive load and supports consistency across learners, while acknowledging that primary school students may experience difficulty articulating nuanced or abstract judgments about their learning characteristics. Consequently, responses are interpreted as indicative signals rather than exact measurements, [10].

The chatbot-based interaction facilitates efficient data collection within regular classroom routines and can be repeated over time with minimal disruption. This enables learner profiles to be updated dynamically as students' interests or preferences evolve, supporting adaptive group formation. By embedding data collection in a conversational interface, the framework provides a practical and scalable mechanism for gathering learner information while preserving the central role of teacher observation and professional judgment.

III. PROBLEM SOLUTION

The problem formulated in the previous section is addressed through an AI-supported fuzzy-logic framework that integrates learner profiling, pedagogical recommendation, and classroom grouping. The proposed solution follows a modular workflow consisting of three main stages: learner profile construction based on chatbot-elicited data, fuzzy inference for generating graded pedagogical recommendations, and group formation aligned with instructional objectives. The following subsections describe each component of the proposed solution in detail.

A. Learner profile construction

Learner profiles are constructed by transforming chatbot-elicited responses into structured representations suitable for adaptive decision support. Each profile is defined by three pedagogically relevant dimensions—learning styles, learning preferences, and interests—which collectively capture how learners tend to engage with instructional activities. These dimensions are selected to balance expressive power with practical feasibility in primary education settings.

Responses collected through the chatbot are mapped to numerical values that reflect degrees of association rather than binary assignments. This mapping enables learner characteristics to be represented as flexible, multidimensional profiles in which multiple tendencies may coexist simultaneously. As a result, learner profiles preserve uncertainty and variability, avoiding rigid categorizations that are misaligned with the developmental characteristics of young learners.

Each learner profile is represented as a compact vector that aggregates the mapped values across the selected dimensions. This vector-based representation allows profiles to be processed efficiently by subsequent fuzzy inference mechanisms, while remaining interpretable for instructional decision-making. Because profiles are derived from simple and repeatable interactions, they can be updated dynamically to reflect changes in learner interests or preferences over time.

Figure 1 illustrates the structure of the learner profile and the key variables used in its construction. The representation serves as the input to the fuzzy inference stage described in the following subsection, enabling the generation of graded pedagogical recommendations aligned with learner characteristics.

Fig. 1: Key variables in student learning profiles.
Source: Created by the authors.

B. Fuzzy inference and pedagogical recommendation

The learner profiles constructed in the previous stage are processed through a fuzzy inference mechanism in order to generate pedagogical recommendations. Fuzzy logic is employed to model uncertainty and partial membership in learner characteristics, allowing instructional suitability to be expressed in graded rather than binary terms, [11], [12], [13]. This approach reflects the fact that learners may simultaneously exhibit multiple tendencies to varying degrees.

Each learner profile vector serves as input to a set of fuzzy rules that associate combinations of learning styles, learning preferences, and interests with pedagogical approaches. The rules follow an IF–THEN structure and are designed to capture pedagogically meaningful relationships between learner characteristics and instructional strategies. Instead of producing a single deterministic outcome, the inference process generates confidence values that indicate the degree of suitability of different teaching approaches for each learner.

The fuzzy inference process aggregates rule activations to produce a ranked set of pedagogical recommendations. These recommendations are interpreted as relative suitability scores rather than prescriptions, enabling teachers to consider multiple instructional options simultaneously. By preserving partial memberships and graded outputs, the system avoids rigid instructional assignments and supports flexible pedagogical decision-making.

Figure 2 illustrates the mapping of learner responses to fuzzy membership values and the overall inference process leading to pedagogical recommendations. The resulting confidence values constitute the input for the grouping mechanism described in the following subsection, where learners are organized into instructional groups aligned with selected teaching strategies.

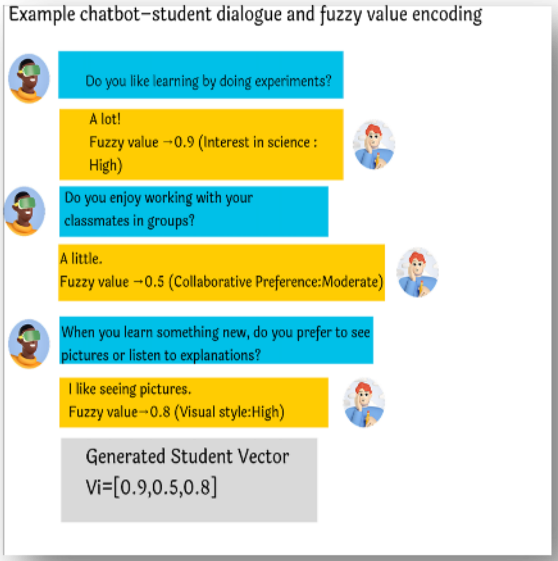

Fig. 2: Mapping Student Responses to Fuzzy Membership Values
Source: Created by the authors.

C. Grouping mechanism and simulation setup

The pedagogical recommendations produced by the fuzzy inference stage are subsequently used to support classroom group formation. Grouping decisions are guided by instructional objectives and can be configured to support either heterogeneous or homogeneous group compositions. In heterogeneous grouping, learners with diverse profiles are intentionally combined in order to promote collaboration, peer learning, and exposure to different perspectives, [14]. In homogeneous grouping, learners with similar profiles are clustered together to support focused instruction and targeted skill development, [15].

The grouping mechanism operates by comparing learner profile vectors and their associated pedagogical recommendation scores. Depending on the selected instructional goal, similarity or diversity criteria are applied to assign learners to groups of predefined size. This process is designed to remain computationally efficient and transparent, enabling teachers to understand and adjust grouping outcomes when necessary.

To examine the feasibility and scalability of the proposed framework, a simulation-based evaluation was conducted across different class sizes, [16]. The simulation compares the proposed fuzzy-logic–based grouping approach with two baseline strategies: random grouping and manual grouping, [17]. Grouping time and group-quality indicators are used as comparative metrics, [18]. Manual grouping time is modeled to increase with class size, reflecting realistic classroom constraints, whereas automated grouping time remains consistently low, [19].

The simulation results indicate that the proposed approach scales efficiently as class size increases, maintaining minimal grouping time while producing group-quality measures that remain consistently higher than those obtained through random grouping, [20]. These findings suggest that the framework can support pedagogically meaningful group formation with reduced organizational effort, particularly in larger classrooms, [21]. Importantly, the simulation is intended to assess algorithmic behavior and design feasibility rather than pedagogical outcomes, which remain the subject of future empirical investigation, [22]. Figure 3 presents the comparison of grouping time and group-quality trends across the proposed, random, and manual grouping strategies.

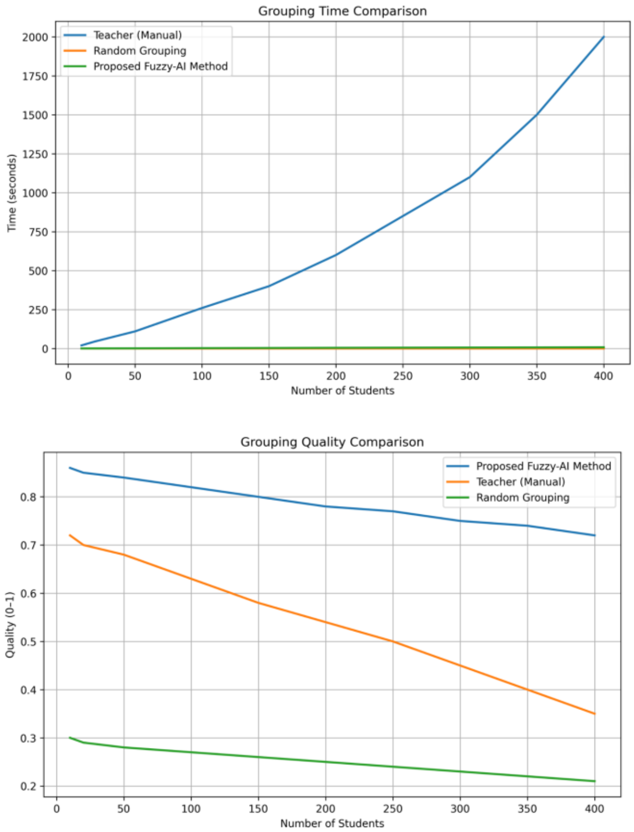

Fig. 3: Comparison of grouping time and group-quality trends for proposed, random, and manual grouping strategies across different class sizes.
Source: Created by the authors.

IV. CONCLUSION

This paper presented a theoretical AI-supported framework that combines fuzzy logic and chatbot-based learner profiling to support classroom grouping and differentiated instruction in primary education. By modeling learner characteristics as flexible and multidimensional profiles, the proposed approach enables graded pedagogical recommendations and adaptive group formation aligned with instructional goals.

A simulation-based analysis demonstrated that the framework scales efficiently across different class sizes, maintaining low grouping time while producing consistently higher group-quality trends compared to random grouping strategies. These findings highlight the potential of fuzzy-logic mechanisms to support pedagogically meaningful grouping decisions with minimal teacher workload.

The proposed framework is intended to complement, rather than replace, teacher judgment by providing transparent and adaptable decision support. Future work will focus on empirical classroom implementation, the integration of teacher feedback, and the evaluation of pedagogical outcomes associated with different grouping strategies.

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Contribution of individual authors to the creation of a scientific article (ghostwriting policy)

Maria Grigori conceived the research idea, designed the theoretical framework, developed the fuzzy-logic model, and drafted the manuscript. Klimis Ntalianis contributed to the conceptual refinement of the framework, provided academic supervision, and critically reviewed the manuscript. Nikos E. Mastorakis contributed to the methodological structuring of the study, provided scientific guidance, and participated in the final revision of the manuscript. All authors have read and approved the final version of the manuscript.

Sources of funding for research presented in a scientific article or scientific article itself

This research received no external funding.

Conflict of Interest

The authors state that they have no financial interests or personal relationships that could affect the work done in this study.