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A HUMAN-CENTERED AI PEDAGOGY FRAMEWORK FOR K–12 LEARNING

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Abstract

The integration of artificial intelligence (AI) in K–12 digital learning environments has increased the potential for adaptive and personalized instruction.However, many AI-driven educational studies still focus on analytical outcomes without clearly translating learner data into pedagogically meaningful instructional decisions. Addressing this gap, this study proposes a human-centered AI pedagogy grounded in learner profiling and instructional interpretation within K–12 English digital learning contexts. A quantitative, data-driven approach was employed using questionnaire data collected from K–12 students across elementary, middle, and high school levels. Learner profiles were identified using Fuzzy C-Means clustering to capture overlapping learner characteristics and transitional learning stages, which were then interpreted pedagogically to examine differences in learning autonomy, instructional support needs, and English learning orientations. Based on this interpretation, an AI-supported instructional decision framework was developed to translate learner profiles into adaptive instructional recommendations while maintaining teacher agency. The findings reveal three distinct yet overlapping learner profiles, highlighting the limitations of rigid, grade-based instructional design and demonstrating how learner profiles can inform differentiated English learning strategies. By positioning AI as an instructional decision-support tool rather than an autonomous teaching agent, this study contributes a practical and ethical approach to AI-driven pedagogy and offers conceptual and practical insights for educators, curriculum designers, and educational technology developers seeking to implement adaptive, teacher-guided AI solutions in K–12 English digital learning environments.

INTRODUCTION

The rapid advancement of artificial intelligence (AI) has reshaped contemporary educational practices, particularly within digital and online learning environments. AI driven systems are increasingly adopted to support adaptive learning, personalized instruction, and data-informed pedagogical decision making in teaching and learning processes. In K-12 digital learning contexts, these developments offer significant potential to address learner diversity; however, they also introduce challenges related to developmental appropriateness, instructional alignment, and the role of teachers in AI supported environments.

Prior research on AI in education has predominantly focused on higher education and adult learning contexts, emphasizing learning analytics, intelligent tutoring systems, and performance optimization. While these studies demonstrate the technical capability of AI to enhance learning efficiency, they often adopt a technology-centered perspective. Such an approach risks overlooking the pedagogical complexity inherent in K–12 education, where learners' cognitive, motivational, and self-regulatory capacities develop progressively across educational stages (Zawacki-Richter et al., 2019).

From a learner,experience perspective, theoretical models such as the Technology Acceptance Model (TAM) (Davis, 1989), Task,Technology Fit (TTF), and the System Usability Scale (SUS) have been widely used to explain how learners interact with learning technologies, emphasizing usability, motivation, satisfaction, and learning outcomes as key predictors of success (Šumak, Heričko, & Pušnik, 2011). However, evidence remains uneven across learner age groups, as many studies have focused on adults, while child,centered digital learning contexts are comparatively less examined (Chuenyindee et al., 2022; Mailizar et al., 2020; Salloum et al., 2019). In addition, prior work has relied predominantly on confirmatory approaches such as structural equation modeling (SEM), with fewer studies employing exploratory, data,driven approaches to reveal latent learner patterns in K-12 settings (Ngampornchai & Adams, 2016; Wang et al., 2023).As such, these models are increasingly used not only to explain technology acceptance, but also to inform instructional interpretation and teaching-related decision making in digital learning contexts.

In parallel, research on adaptive instruction underscores the value of learner profiling as a foundation for personalization. Clustering techniques have been increasingly adopted in educational research to identify heterogeneous learner groups and uncover latent behavioral patterns, including in K–12 English digital learning contexts where learner characteristics evolve from guided and gamified learning experiences toward higher autonomy and task-based engagement.. Yet, many studies treat profiling outcomes as analytical endpoints, with limited guidance on translating AI-derived learner profiles into concrete pedagogical actions that can support teachers' instructional decision making.

To ensure theoretical rigor in the measurement of learners' experiences in digital learning environments, this study adopts a questionnaire framework grounded in established models of technology acceptance and task–technology alignment. The framework integrates key constructs related to learners' perceptions of system usability, usefulness, task–technology fit, satisfaction, and attitudes toward online learning systems. Rather than treating these constructs as independent indicators, the framework conceptualizes their interrelationships as a basis for understanding heterogeneous learner experiences in technology-enhanced learning contexts. Figure 1 presents the conceptual framework used to guide questionnaire design and variable selection, adapted from prior validated research, and serves as the theoretical foundation for subsequent learner profiling and clustering analysis.

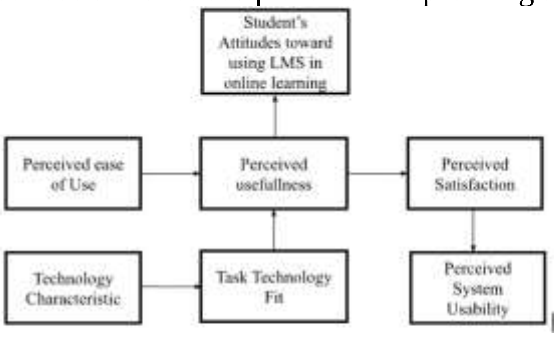

Figure 1. Conceptual framework for clustering variables (adapted from Chuenyindee et al., 2022)

Recent scholarship further highlights the importance of human-centered AI, positioning AI as an instructional decision-support mechanism rather than an autonomous teaching agent. Teacher-in-the-loop approaches emphasize the preservation of teachers' professional judgment, ensuring that AI-supported recommendations remain aligned with curricular goals, contextual constraints, and pedagogical accountability (Luckin et al., 2022; Balaji et al., 2025). Complementarily, human-in-the-loop adaptive learning designs stress the role of continuous feedback from teachers and learners in refining AI-supported instructional recommendations over time (Tarun et al., 2025). Together, these perspectives underscore that effective instructional adaptation requires the integration of data-driven insights with explicit human agency.

Despite these advances, limited research has systematically integrated data-driven learner profiling with literature-grounded AI-supported instructional decision frameworks in K–12 English digital learning contexts. In particular, there remains a gap between exploratory learner profiling results and their operationalization into pedagogically meaningful, teacher-centered instructional strategies.

Therefore, this study aims to identify latent learner profiles in K–12 English digital learning using Fuzzy C-Means clustering and to extend these profiling results toward a human-centered, AI-supported instructional decision framework to support teachers' instructional planning and pedagogical decision making.

The novelty of this study lies in three key contributions. First, rather than treating learner profiling as an analytical endpoint, this study explicitly translates Fuzzy C-Means clustering results into pedagogically meaningful learner readiness profiles that can inform instructional decisions. Second, the proposed framework integrates data-driven learner profiling with human-centered AI principles, positioning AI as an instructional decision-support layer rather than an autonomous instructional agent. Third, the study situates this integration within K–12 English digital learning contexts, offering a teaching-oriented perspective that bridges learner analytics and instructional practice.

By translating learner profiles into pedagogically meaningful interpretations and mapping them to literature-informed AI-supported instructional strategies, this study contributes to the discourse on AI-driven pedagogy and instructional innovation while maintaining teachers' central role in K–12 English education.

METHOD

Research Design

This study employed a quantitative, data-driven research design with an exploratory orientation to support AI-driven pedagogical innovation in K–12 digital learning. The methodological approach emphasizes learner profiling and pedagogical interpretation rather than algorithm comparison. AI is positioned as an instructional decision-support mechanism that augments teachers' professional judgment instead of functioning as an autonomous instructional agent, consistent with human-centered and teacher-in-the-loop perspectives in artificial intelligence in education (Zawacki-Richter et al., 2019; Luckin et al., 2022).
The overall research workflow of the study, including data collection, preprocessing, clustering analysis, pedagogical interpretation, and AI-supported instructional decision synthesis, is illustrated in Figure 2.

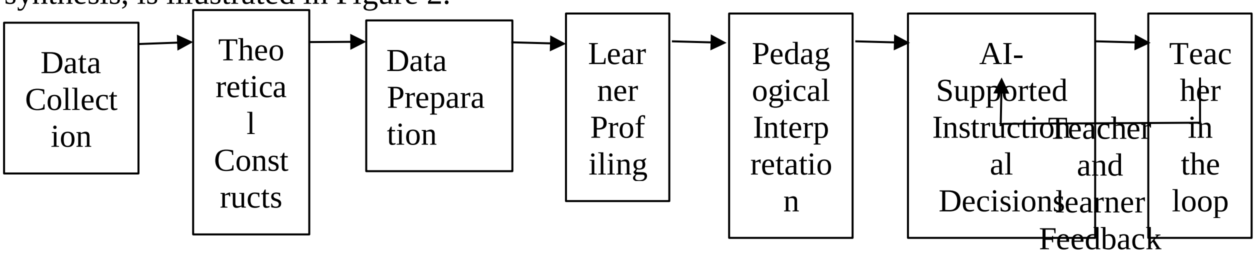

Figure 2 . Research workflow from learner data collection to AI-supported instructional decisions with teacher-in-the-loop feedback

Participants and Data Collection

The dataset consisted of responses from 450 K–12 students across three educational levels: elementary, middle, and high school. Participants were drawn from technology-enhanced digital learning environments where English learning activities were delivered through digital instructional platforms. Data were collected using structured questionnaires designed to capture learners' perceptions and experiences with digital learning systems.

The questionnaire items were developed based on established learner experience and technology acceptance constructs, including perceived usability, learning engagement, motivation, satisfaction, and task–technology alignment. An overview of the questionnaire constructs and measurement indicators used in this study is presented in Table 1.

Table 1. Questionnaire constructs used in this study

Construct	Description	Sample Indicator	Source
Perceived Ease of Use	Degree to which learners perceive the system as easy to use	Ease of navigation, clarity of interface	Davis (1989)
Perceived Usefulness	Extent to which the system enhances learning performance	Learning effectiveness, task support	Davis (1989)
Task–Technology Fit	Alignment between learning tasks and system features	Task suitability, feature relevance	Goodhue & Thompson (1995)
Learner Satisfaction	Learners' overall satisfaction with the learning system	Enjoyment, contentment	Šumak et al. (2011)
System Usability	Overall usability of the digital learning system	Efficiency, effectiveness, ease	Brooke (1996)
Attitude Toward LMS	Learners' attitude toward using LMS in online learning	Willingness to use, positive perception	Chuenyindee et al. (2022)

Data Preparation

Prior to analysis, the dataset was screened for completeness and consistency. Responses were standardized to ensure comparability across variables and educational levels. Descriptive statistics were employed to examine overall response distributions and confirm the suitability of the data for clustering analysis. This preprocessing step ensured that subsequent learner profiling reflected meaningful variations in learner experience rather than scale-related measurement artifacts, consistent with practices in adaptive learning research (Gligorea et al., 2023).

Learner Profiling Using Fuzzy C-Means Clustering

Fuzzy C-Means (FCM) clustering was applied to identify latent learner profiles based on selected learner experience variables. FCM was selected because it allows learners to belong to multiple clusters with varying degrees of membership, which is well suited for adaptive learning contexts characterized by heterogeneous learner characteristics and gradual transitions in learning behavior (Gligorea et al., 2023). Overlapping cluster membership was interpreted as an indicator of transitional learning stages rather than analytical noise, consistent with human-in-the-loop perspectives on learner modeling (Memarian & Doleck, 2024).

The number of clusters was set to three to represent pedagogically meaningful groupings aligned with different levels of learning autonomy and instructional support. Key clustering parameters and configuration settings used in the FCM analysis are summarized in Table 2. The clustering output produced cluster centroids representing dominant learner characteristics, along with membership values indicating each learner's degree of association with each profile. These outputs served as the analytical foundation for subsequent pedagogical interpretation.

Table 2. Fuzzy C-Means Clustering Configuration and Parameters

Parameter	Description	Value/Setting
Number of clusters (K)	Predefined number of learner profiles	3
Clustering method	Fuzzy clustering technique	Fuzzy C-Means
Fuzziness coefficient (m)	Degree of cluster overlap	2.0
Distance measure	Metric used to compute similarity	Euclidean distance
Stopping criterion	Convergence threshold	$\varepsilon = 0.001$
Maximum iterations	Upper limit for algorithm iteration	100
Output	Clustering results	Membership matrix and centroids

Pedagogical Interpretation of Learner Profiles

The identified learner profiles were interpreted through a pedagogical lens to examine differences in instructional needs, learner autonomy, and support requirements. This interpretive step extends beyond technical clustering results by translating learner data into instructional meaning. Overlapping membership patterns were analyzed as signals of instructional flexibility needs, particularly for learners transitioning between guided and autonomous learning modes. This approach aligns with adaptive learning literature emphasizing pedagogical interpretation over purely technical performance metrics (Strielkowski et al., 2025; Gligorea et al., 2023).

AI-Supported Instructional Decision Framework

The AI-supported instructional decision framework proposed in this study is derived from a focused review of recent literature on human-centered AI, adaptive learning, and teacher-in-the-loop approaches (Luckin et al., 2022; Balaji et al., 2025; Tarun et al., 2025). Rather than implementing an autonomous AI system, the framework adopts established theoretical principles to guide how AI-informed insights can support instructional decision making in K–12 English digital learning contexts, where pedagogical accountability and developmental appropriateness are critical considerations (Zawacki-Richter et al., 2019).

Within this framework, AI is positioned as an instructional recommendation layer that synthesizes learner profiling results to inform pedagogical choices. Specifically, AI-supported insights are used to assist teachers in adjusting content sequencing, determining appropriate levels of instructional scaffolding, and selecting task complexity aligned with learners' readiness and engagement levels (Gligorea et al., 2023; Strielkowski et al., 2025). These recommendations are intended to support reflective instructional planning rather than automate teaching processes.

A central principle of the framework is the teacher-in-the-loop approach, which ensures that teachers retain full authority over instructional decisions. In line with human-centered AI perspectives, AI-generated recommendations are subject to teachers' professional judgment, contextual knowledge of learners, and alignment with curriculum objectives (Luckin et al., 2022; Balaji et al., 2025). Teachers may accept, modify, or disregard AI-supported suggestions based on classroom dynamics and pedagogical considerations.

The framework further incorporates a feedback mechanism in which teachers' instructional decisions and learners' responses inform subsequent AI-supported recommendations. This feedback loop is conceptual and does not involve automated model retraining; instead, it supports continuous pedagogical reflection and adaptive instruction while preserving human agency (Tarun et al., 2025; Khosravi et al., 2022).

Overall, this AI-supported instructional decision framework serves as a conceptual bridge between data-driven learner profiling and practical instructional adaptation. By grounding AI-supported decisions in prior research and embedding teacher agency at the core of the process, the framework demonstrates how AI-informed insights can be responsibly integrated into K–12 English language teaching practices (Gligorea et al., 2023; Luckin et al., 2022).

Framework Validation (Scenario-Based Validation)

To validate the applicability of the proposed AI-supported instructional decision framework, a scenario-based validation approach was employed. This approach is commonly used in conceptual and design-oriented educational research to examine the practical plausibility of frameworks without requiring system implementation or large-scale experimental deployment. Validation was conducted by mapping representative learner profiles identified through Fuzzy C-Means clustering to instructional scenarios in K–12 English digital learning contexts.

Three instructional scenarios were constructed to correspond with the guided, transitional, and autonomous learner profiles. For each scenario, learner characteristics, AI-supported instructional recommendations, and teacher decision points were examined in relation to existing literature on human-centered AI, adaptive learning, and teacher-in-the-loop pedagogy. This process allowed the framework to be evaluated in terms of pedagogical coherence, instructional relevance, and alignment with teacher-centered decision making, rather than technical performance metrics.

FINDINGS AND DISCUSSION

Learner Profiling Using Fuzzy C-Means

The application of Fuzzy C-Means clustering identified three learner profiles within K–12 digital learning environments. The selection of three clusters was supported by the elbow method, which indicated diminishing variance reduction beyond this point, suggesting an optimal balance between model simplicity and explanatory power (see Figure 3). This configuration reflects pedagogically meaningful differentiation rather than purely statistical optimization.

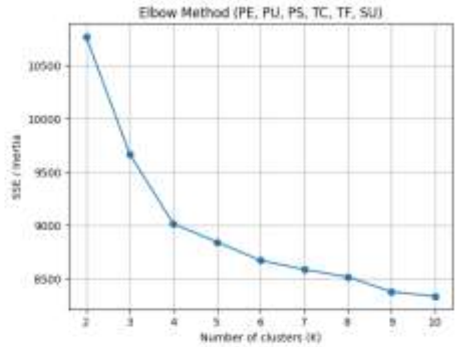

Figure 3. Elbow plot demonstrating that K = 3 provides the most stable balance between within-cluster variance and model parsimony.

The FCM clustering visualization illustrates overlapping membership patterns among learners across profiles (see Figure 4). The results indicate that learner development in K–12 digital learning contexts is continuous and fluid, supporting the use of fuzzy clustering for modeling heterogeneous learner populations.

Figure 4. Visualization of learner clustering using Fuzzy C-Means algorithms

The dominant characteristics associated with each learner profile are summarized in Table 3. The first profile represents learners who rely heavily on structured guidance and explicit instructional support. The second profile captures transitional learners who demonstrate balanced engagement, combining emerging autonomy with continued scaffolding needs. The third profile consists of learners who exhibit high autonomy and readiness for independent learning tasks.

Table 3. Learner Profile Characteristics Based on Fuzzy C-Means Clustering

Learner Profile	Dominant Characteristics	Learning Autonomy Level	Instructional Support Needed
Guided Learners	High reliance on guidance, low self-regulation	Low	High

Transitional Learners	Mixed engagement, emerging self-regulation	Medium	Moderat e
Autonomous Learners	High independence, strong self-regulation	High	Low

Pedagogical Interpretation of Learner Profiles

To address the gap between analytical profiling and instructional application, the identified learner profiles were interpreted from a pedagogical perspective. This interpretation moves beyond descriptive segmentation by translating clustering outcomes into instructional meaning.

As illustrated in Figure 5, learners in the guided profile benefit from structured instruction, explicit task sequencing, and frequent feedback. In English learning contexts, this includes guided vocabulary practice, scaffolded reading activities, and teacher-led language modeling. Transitional learners require adaptive instructional strategies that gradually reduce scaffolding while introducing task-based and collaborative English learning activities. Learners in the autonomous profile demonstrate readiness for project-based learning, inquiry-oriented tasks, and independent English communication.

This pedagogical interpretation aligns with adaptive learning research emphasizing instructional differentiation based on learner readiness and engagement rather than fixed categorization (Gligorea et al., 2023; Strielkowski et al., 2025).

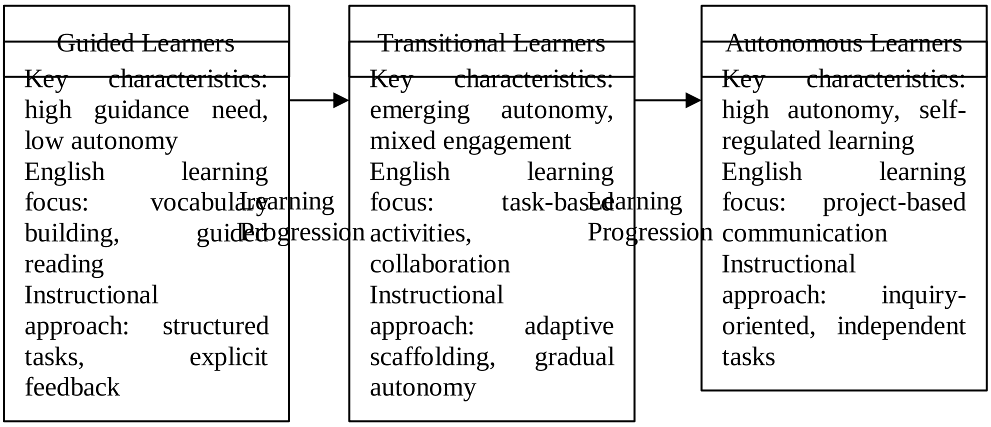

Figure 5. Pedagogical interpretation of K–12 learner profiles

AI-Supported Instructional Decision Framework

Building on the pedagogical interpretation of learner profiles, an AI-supported instructional decision framework was developed to translate empirical profiling results into instructional actions. As illustrated in Figure 6, the framework integrates data-driven learner profiling with literature-based principles of adaptive learning and human-centered AI.

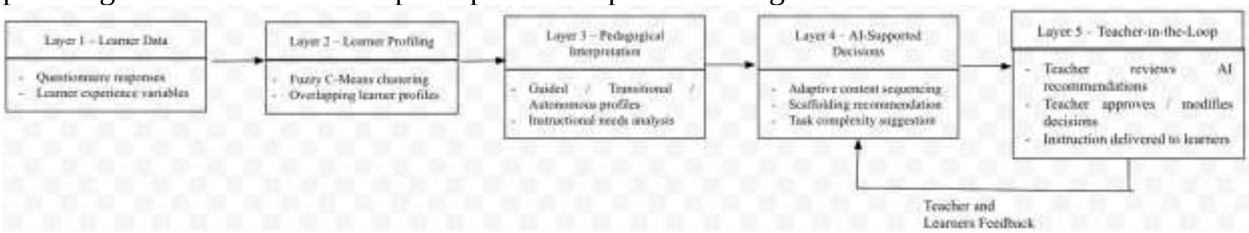

Figure 6. AI-supported instructional decision framework integrating learner profiling, pedagogical interpretation, and teacher-in-the-loop principles

Within this framework, Layers 1 and 2 are derived directly from the empirical analysis conducted in this study, encompassing questionnaire-based learner data and Fuzzy C-Means learner profiling results. Layer 3 represents the pedagogical interpretation of the identified profiles, where data-driven patterns are translated into instructional needs associated with guided, transitional, and autonomous learners.

In contrast, Layers 4 and 5 are grounded in prior literature on adaptive learning, human-centered AI, and teacher-in-the-loop approaches. At this stage, AI is positioned as an instructional recommendation layer that supports, rather than replaces, teachers' pedagogical decision making (Luckin et al., 2022; Khosravi et al., 2022; Balaji et al., 2025; Tarun et al., 2025). AI-supported actions include adaptive sequencing of English learning materials, recommendations for instructional scaffolding, and suggestions for task complexity aligned with learner readiness.

The mapping between learner profiles, AI-supported instructional actions, and teacher roles is summarized in Table 4. In this mapping, learner profiles and their characteristics originate from the empirical clustering results, while the proposed AI-supported actions and teacher-in-the-loop roles are synthesized from prior literature.

Table 4. Mapping Learner Profiles to AI-Supported Instructional Decisions

Learner Profile	AI - Supported Insight	AI-Supported Instructional Decision	Teacher Role
Guided Learners	High need for structure and guidance	Recommend scaffolded content and step-by-step tasks	Review recommendations, adjust pacing and support level
Transitional Learners	Mixed readiness and emerging autonomy	Recommend adaptive tasks with gradual reduction of scaffolding	Fine-tune task difficulty and scaffolding
Autonomous Learners	High independence and self-regulation	Recommend open-ended and project-based tasks	Monitor progress and provide targeted feedback

Teachers remain the central decision makers within the framework. AI-generated recommendations are intended to inform instructional judgment rather than replace it. This positioning reflects human-centered and teacher-in-the-loop approaches that emphasize pedagogical accountability and professional agency (Luckin et al., 2022; Balaji et al., 2025; Tarun et al., 2025).

Scenario-Based Validation Results

The scenario-based validation indicates that the proposed framework provides coherent instructional guidance across different learner readiness profiles. For guided learners, AI-supported recommendations emphasize high levels of instructional scaffolding, structured content sequencing, and explicit learning support. In these scenarios, teachers retain control over pacing and instructional strategies, using AI recommendations as reference points rather than prescriptive directives.

For transitional learners, the framework supports gradual reduction of scaffolding and increased task complexity. AI-supported suggestions focus on adaptive sequencing and balanced instructional support, while teachers determine when learners are ready to transition

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toward greater autonomy. This aligns with developmental perspectives emphasizing progressive learner independence in K–12 education.

For autonomous learners, AI-supported recommendations prioritize minimal scaffolding, project-based tasks, and higher-order English learning activities. Teachers use AI insights to monitor learner readiness and adjust instructional challenges, ensuring alignment with curriculum objectives. Across all scenarios, the validation demonstrates that AI functions consistently as an instructional decision-support layer, while teachers remain the primary decision makers within the learning process.

Discussion

The findings of this study extend prior research on learner profiling and AI-supported pedagogy by demonstrating how data-driven analysis can be systematically translated into pedagogically meaningful instructional decisions in K–12 English digital learning contexts. Rather than treating learner profiling as an analytical endpoint, the results highlight its value as a foundation for pedagogical reasoning, particularly in environments characterized by developmental diversity and overlapping learner characteristics.

The identification of guided, transitional, and autonomous learner profiles reflects progressive stages of learner readiness commonly observed in K–12 education. This interpretation responds to longstanding concerns in learner analytics research, where clustering outcomes are frequently reported without clear instructional relevance (Gligorea et al., 2023; Strielkowski et al., 2025). By explicitly linking learner profiles to differentiated instructional needs, the study demonstrates how exploratory profiling methods such as Fuzzy C-Means can support instructional planning rather than remain descriptive in nature.

The discussion further clarifies the role of artificial intelligence within this instructional process. While much of the AI-in-education literature continues to emphasize technology-driven optimization, emerging scholarship increasingly argues for human-centered approaches that preserve pedagogical accountability (Zawacki-Richter et al., 2019; Luckin et al., 2022). Consistent with this perspective, the proposed framework conceptualizes AI as an instructional decision-support layer rather than an autonomous teaching agent. AI-supported recommendations related to content sequencing, scaffolding intensity, and task complexity are positioned as inputs to teachers' professional judgment, aligning with teacher-in-the-loop and human-in-the-loop models (Balaji et al., 2025; Tarun et al., 2025).

An important contribution of this study lies in its integration of empirical learner profiling with literature-grounded AI-supported instructional principles. Previous studies have often treated empirical learner data and pedagogical frameworks as separate strands, resulting in limited operational guidance for instructional practice (Khosravi et al., 2022). By synthesizing data-driven learner profiles with established concepts from adaptive learning and human-centered AI research, the proposed framework illustrates how empirical evidence and theoretical insights can be operationalized within a coherent instructional decision structure, as reflected in Figure 6 and Table 4.

The scenario-based validation further demonstrates that the proposed framework can be plausibly applied across varying learner readiness levels in K–12 English digital learning, reinforcing its pedagogical coherence without relying on autonomous AI implementation.

Finally, situating the framework within K–12 English digital learning contexts extends existing AI-supported adaptive learning research beyond higher education and domain-general applications. English learning involves gradual development of linguistic competence, communicative confidence, and learner autonomy, making instructional sequencing and scaffolding particularly critical. Prior studies have shown that AI-supported personalization can enhance English learning outcomes when aligned with learner readiness and instructional goals (Wang et al., 2024). The present study extends this line of research by demonstrating how learner profiles can guide teachers in applying AI-supported instructional decisions that remain sensitive to developmental stages in K–12 English education.

Overall, the discussion underscores that the pedagogical value of AI in K–12 education lies not in algorithmic sophistication alone, but in its alignment with learner development and teacher-centered instructional practice. By bridging learner profiling, pedagogical interpretation, and AI-supported instructional decision making, this study contributes a human-centered framework for AI-driven instructional innovation that remains grounded in professional judgment and educational context.

CONCLUSION AND SUGGESTION

This study demonstrates how learner profiling using Fuzzy C-Means clustering can be extended beyond analytical segmentation to support pedagogically meaningful decision making in K–12 English digital learning contexts. By identifying overlapping learner profiles, the findings highlight that learner development is continuous and cannot be effectively addressed through rigid, grade-based instructional strategies alone.

The pedagogical interpretation of learner profiles shows that different levels of learning autonomy and support needs require differentiated instructional approaches. Rather than treating clustering outcomes as descriptive endpoints, this study illustrates how learner data can be translated into instructional meaning that informs teaching practice. This translation is essential for ensuring that data-driven insights contribute to real instructional improvement.

Furthermore, the proposed AI-supported instructional decision framework positions AI as a supportive recommendation layer that assists teachers in adapting instruction while preserving professional judgment and pedagogical accountability. By emphasizing human-centered and teacher-in-the-loop principles, the framework addresses concerns related to over-automation and aligns AI use with educational values.

In the context of English learning, the findings suggest that AI-supported personalization can be more effective when grounded in learner profiles and guided by teachers' pedagogical reasoning. Overall, this study contributes to the discourse on AI-driven pedagogy by offering a practical and ethical approach that connects learner profiling, instructional differentiation, and AI-supported decision making in K–12 digital learning environments.

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