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MULTILEVEL ADAPTIVE HUMAN–AI TEACHING MODEL FOR HYBRID CLASSROOMS

МНОГОУРОВНЕВАЯ АДАПТИВНАЯ МОДЕЛЬ НА ОСНОВЕ ВЗАИМОДЕЙСТВИЯ С ИСКУССТВЕННЫМ ИНТЕЛЛЕКТОМ В УСЛОВИЯХ ГИБРИДНОГО ОБУЧЕНИЯ

Abstract:

This research aims to develop a multi-level adaptive learning framework based on collaboration between human teachers and artificial intelligence (AI). It is grounded in a targeted review of the scientific literature on personalized learning, learning analytics, and coordination of classroom instruction. The framework comprises three interconnected levels. At the individual (micro) level, the AI teacher adapts instruction to each learner's needs. At the intermediate (meso) level, learners' educational data are examined collectively to identify common difficulties and their potential causes. Based on this information and the pedagogical context, it is proposed to separately select the intervention level—individual, small-group, or whole-class—and the implementer: the AI teacher, the human teacher, or their joint participation. At the classroom (macro) level, the human teacher organizes general instruction and retains final decision-making authority and responsibility. Following each intervention, provision is made to individually reassess the learner's educational outcomes and organize subsequent instruction based on them, while maintaining their individual learning trajectory. The potential scientific contribution of the framework lies in linking individual adaptation, student data aggregation, and the organization of classroom interventions within a continuous decision-making system. The effectiveness of the model has not yet been confirmed and is subject to further empirical verification.

The scientific novelty of the study lies in the development of a principle for determining separately the level of pedagogical intervention (micro, meso, or macro) and the agent responsible for its implementation (artificial intelligence, the human teacher, or their joint participation) within a unified adaptive learning cycle that enables continuous adjustment of the educational process based on the individual assessment of learners’ outcomes.

Keywords: adaptive learning, artificial intelligence, personalized learning, human–AI collaboration, multi-level instructional coordination, learning progress assessment, pedagogical intervention, teacher–AI co-regulation

Аннотация:

Цель исследования — разработать многоуровневую адаптивную модель обучения, основанную на сотрудничестве преподавателя и искусственного интеллекта (ИИ). Теоретической основой исследования послужил целенаправленный обзор научной литературы, посвящённой персонализированному обучению, аналитике образовательных данных и координации учебного процесса в классе.

Предлагаемая модель включает три взаимосвязанных уровня. На индивидуальном (микро-) уровне ИИ-преподаватель адаптирует обучение к потребностям каждого обучающегося. На промежуточном (мезо-) уровне образовательные данные обучающихся анализируются в совокупности с целью выявления общих затруднений и их возможных причин. На основе полученных данных и с учётом педагогического контекста предлагается раздельно определять уровень педагогического вмешательства — индивидуальный, групповой или общеклассный — и его исполнителя: ИИ-преподавателя, человека-преподавателя либо их совместное участие. На уровне класса (макроуровне) преподаватель организует учебный процесс в целом, сохраняя за собой полномочия по принятию окончательных решений и ответственность за них. После каждого педагогического вмешательства предусматривается индивидуальная повторная оценка образовательных результатов обучающегося и последующая организация обучения с учётом полученных данных при сохранении его индивидуальной образовательной траектории. Потенциальный научный вклад предложенной модели заключается в объединении индивидуальной адаптации обучения, агрегирования данных об обучающихся и организации педагогических вмешательств в рамках непрерывной системы принятия решений. Эффективность модели пока не подтверждена и требует дальнейшей эмпирической проверки.

Научная новизна исследования заключается в разработке принципа раздельного определения уровня педагогического вмешательства (микро-, мезо- и макроуровень) и субъекта его реализации (искусственный интеллект, преподаватель или их совместное участие) в рамках единого цикла адаптивного обучения, обеспечивающего непрерывную корректировку образовательного процесса на основе индивидуальной оценки результатов обучающихся.

Ключевые слова: адаптивное обучение, искусственный интеллект, персонализированное обучение, взаимодействие человека и искусственного интеллекта, многоуровневая координация обучения, оценка динамики образовательных результатов, педагогическое вмешательство, совместная регуляция обучения преподавателем и искусственным интеллектом

1. Introduction

The traditional classroom teaching model enables a single teacher to organize the general learning process for students within a given subject. However, within the same classroom, each learner possesses unique characteristics and differs from others in their capabilities: prior knowledge, mastery level, work pace, support needs, and so forth. A human teacher also has limited time and attention, making it difficult to simultaneously and continuously monitor each learner's

educational progress, identify their difficulties, select appropriate support, and subsequently verify whether it yielded the desired outcome [1].

AI-driven adaptive and intelligent tutoring systems enhance the opportunities for personalized learning [1, 8–10, 13, 14]. Based on a learner's responses, errors, trial attempts, and other educational data, these systems can evaluate their current learning state and adapt the instructional content accordingly by selecting the appropriate task, presentation format, complexity, hint, or feedback. Thus, an AI teacher can simultaneously support diverse learners, each with their own educational needs, pace of progress, and individual learning trajectory.

However, another challenge arises here. If the AI teacher works with numerous students simultaneously in a classroom and tailors each student's instruction to their individual needs, it is also necessary to understand how these individual processes connect to the classroom's overall instruction and progress. Despite learning personalization, students remain within the same classroom system. For example, if a learning difficulty on a specific topic is detected in only a single student, an individual intervention may suffice. If the same or a related difficulty is identified in a specific group of students, small-group work may be necessary. And if the issue concerns the majority of the class, a whole-class intervention may be more appropriate.

Research on human–AI hybrid learning has already explored various aspects of this problem [1, 2, 4–7, 18, 21]. Studies have examined the division of roles between the human teacher and the AI teacher, AI-provided support for the teacher, transitions between individual, small-group, and whole-class instruction, as well as collaboration and responsibility sharing between the human teacher and the AI teacher. However, it is necessary to integrate these components into a single overarching system and demonstrate how educational data from various students can be analysed and aggregated, how to determine, based on this data, who needs an intervention, in what form and scope it should be carried out, who should execute it—the AI teacher, the human teacher, or both jointly—and who should make the final decision in a given situation.

The proposed study links individual learning, student data aggregation, and the organization of classroom work. The level of intervention and the implementer are chosen separately, and outcomes are reassessed individually.

1.1. Research Aim

The aim of this research is to develop a Human–AI Multi-Level Adaptive Learning framework that integrates and coordinates the learning process at the individual, small group, and whole-class levels, alongside the principles of human–AI collaboration within a hybrid learning model.

1.2. Research Objectives

- Develop a unified framework that integrates personalized learning for each student, the analysis and aggregation of student educational data, and the coordination of whole-class instruction.
- Define the principles for selecting the pedagogical intervention level (individual, small-group, or whole-class) and its implementer (AI teacher, human teacher, or their joint participation).
- Define the principles for individual knowledge reassessment after a pedagogical intervention, the subsequent instruction based on the results, and the distribution of functions between the AI teacher and the human teacher—preserving the student's individual learning trajectory and the human teacher's ultimate decision-making right and responsibility.

1.3. Scientific Novelty

AI-driven personalized learning [8–10, 13, 14], the joint organization of individual, group, and classroom work [4, 19, 22], and human–AI collaboration [5, 7] have already been studied. The scientific contribution of this research lies in proposing a multi-level conceptual model for their interconnection.

The model provides for determining the following based on the analysis of student educational data:

- **The level of intervention:** individual, small-group, or whole-class.
- **The implementer of the intervention:** the AI teacher, the human teacher, or their joint participation.

Following each intervention, provision is made to separately reassess students' knowledge and organize their subsequent instruction based on the outcomes while maintaining their individual learning trajectory.

Thus, adaptation applies to individual instruction as well as to the organization of group and classroom work. The model is conceptual and subject to empirical verification.

2. Theoretical Foundations of the Framework

2.1. From Individual Adaptive Learning to a Human–AI Classroom System

Research on adaptive learning and intelligent tutoring systems demonstrates that a student's responses, errors, and other observable educational data can be used to assess their knowledge and learning needs and to select the next instructional step [1, 8–10]. In a hybrid learning model, these functions can be distributed between the AI teacher and the human teacher, taking into account their complementary capabilities [1, 7, 11]. Approaches to the educational application of generative AI also emphasize the importance of aligning it with pedagogical goals [16, 17].

When multiple students in the same classroom have different learning trajectories, beyond individual adaptation, it is also necessary to coordinate their general educational activities. The challenge here is not only selecting the next step for each student, but also determining when individual, small-group, or whole-class work is required, and how to connect it with the students' subsequent individual learning. Consequently, the focus of research expands from individual student instruction to the organization of the classroom's overall educational process.

2.2. From AI Support to Human–AI Co-Regulation and Classroom Organization

In research on human–AI hybrid learning, four directions can be distinguished that are crucial for developing the proposed system. The first direction concerns supporting the human teacher through AI. AI systems can collect and analyse student educational data, present their progress, and help the teacher notice difficulties requiring intervention [2, 12, 15]. In the second direction of research, AI not only presents data but also helps identify general learning problems and suggest potential pedagogical interventions [3].

The third direction relates to organizing individual, small-group, and whole-class learning in the classroom. This connects to the Response to Intervention (RTI) approach [23]; however, while tiers in RTI refer to support intensity, here the levels refer to the scope of the intervention (individual, group, or class). These studies investigate how to transition between work levels during instruction, taking into account student needs and lesson flow [4, 19, 22]. The fourth direction is human–AI co-regulation of the learning process. The core question here is what decisions AI can

make, when the human teacher should intervene, and how their functions and responsibilities should be distributed [5, 18, 20, 21].

These studies establish an important foundation for organizing hybrid learning. However, merely collecting student data and presenting it to the teacher is insufficient. If the human teacher is forced to independently examine each student's data and determine all necessary interventions, their workload may increase further [18, 21]. Therefore, the AI system should help not only in identifying learning difficulties but also in suggesting the appropriate intervention level based on them—individual, small-group, or whole-class—and the implementer: the AI teacher, the human teacher, or joint human–AI execution. Simultaneously, the human teacher must retain the right and responsibility to evaluate proposed decisions, modify them when necessary, and make the final decision.

2.3. Research Approach to Framework Development

The aim of this research is to develop a Human–AI Multi-Level Adaptive Learning framework. The work is theoretical in nature and does not include experimental testing of the proposed system's effectiveness. To develop the framework, research on adaptive learning, intelligent tutoring systems, AI-driven teacher support, hybrid learning, and human–AI co-regulation was examined and synthesized. The work is not a systematic literature review; studies directly related to individual adaptation, classroom coordination, and human–AI role allocation were selected for targeted analysis. This selection does not imply an exhaustive coverage of all publications.

The core question of the analysis is: if an AI teacher simultaneously conducts individual adaptive learning for numerous students in the same classroom, what conditions and functions are necessary to organize these processes within a single classroom system? Based on the synthesis of research and problem analysis, five core requirements were identified:

- Continuously assess each student's progress and adapt instruction based on their educational data.
- Analyse and aggregate educational data from different students to identify individual, group, or whole-class learning difficulties.
- Determine the appropriate intervention level (individual, small-group, or whole-class) based on identified difficulties, and select the implementer: the AI teacher, the human teacher, or joint human–AI.
- Ensure the transfer of functions and, where necessary, control between the AI teacher and the human teacher, while retaining final decision-making authority and responsibility with the human teacher.
- Following each intervention, individually reassess the student's learning outcome and determine subsequent instruction based on it, maintaining their individual learning trajectory and connection to the classroom's overall educational process.

These five requirements stem from the synthesis of literature on individual adaptation [8–10], data aggregation [2, 12, 15], classroom transitions [4, 19, 22], human–AI co-regulation [5, 7, 21], and the need for feedback, respectively. The final requirement—the complete cycle of individual post-intervention reassessment and organization of subsequent instruction—represents the proposed solution of this article, rather than an already established finding in the cited sources.

3. Human–AI Multi-Level Adaptive Learning Framework

The framework comprises three interconnected levels: micro (individual student learning), meso (data aggregation and intervention selection), and macro (organization of overall classroom work with final human teacher responsibility). The outcomes of each level are utilized for subsequent decisions.

3.1. Micro-Level: Individual Adaptive Student Learning

At the micro-level, the AI teacher organizes the instruction of individual students, taking into account their knowledge, learning needs, and progress. This approach builds upon research into adaptive learning and intelligent tutoring systems [1, 8–10]. Student responses, errors, task attempt histories, hint usage, and other educational data provide means to evaluate current knowledge and difficulties. However, these data are not direct and infallible measurements of student knowledge; evaluations based on them may be uncertain.

Based on assessment outcomes, the AI teacher can select the student's next instructional step by offering an appropriate task, additional explanation, hint, remedial exercise, or more advanced task. The goal of this process is to secure an individual learning trajectory for every student. In the proposed framework, the significance of the micro-level is not restricted to individual tutoring; it also supplies educational data regarding student progress and difficulties, which are forwarded to the meso-level for comparison with data from other learners. Thus, the micro-level simultaneously adapts individual learning and provides data for subsequent classroom-level instructional organization.

3.2. Meso-Level: Analysing learning data across students

The meso-level bridges individual adaptive learning with general classroom instruction organization. At this level, the AI system analyses and compares educational data from diverse learners to identify which difficulties are characteristic of individual students, which occur within a specific group, and which are widespread across the entire class. However, data aggregation does not mean simply counting how many students made the same mistake. The same error can stem from different causes, and different errors may be driven by the same knowledge gap. Consequently, it is necessary to analyse not only error frequencies but also their potential causes, interrelations, and impact on future learning.

For instance, if several students struggle to solve different tasks, but these difficulties are rooted in the lack of the same prior knowledge, the system can treat them as a shared learning issue. Conversely, if students make superficially identical errors for different reasons, distinct interventions may be needed. When evaluating the significance of learning difficulties, factors such as prevalence, severity, recurrence frequency, the importance of the given knowledge for future learning, as well as available data sufficiency and estimation uncertainty can be taken into account. Cross-learner data analysis is not an entirely novel approach in itself [2, 3, 12, 15]. In the proposed framework, its primary function is to transform individual student educational data into information upon which an appropriate pedagogical intervention can be selected. At the same time, the system cannot unerringly determine causes solely from student errors; these must be treated as data-backed hypotheses that can be additionally verified by the AI teacher or human teacher when necessary. Thus, the meso-level translates individual student educational data into the basis for classroom-level intervention decisions, while the selection process for intervention level and implementer is detailed in the following subsection.

3.3. Selection of Intervention Level and Implementer

Identifying a pattern of learning gaps does not automatically determine the intervention. Guidance can be formally represented in a generalized form as R(X, C) → (L, A), where X represents aggregated student data, C the pedagogical context, L the intervention level, and A the implementer. This is a conceptual definition, not a validated algorithm. In the proposed model, decision-making involves two interconnected yet distinct components: selecting the intervention level and selecting the implementer. The intervention level defines whether the intervention is carried out at the individual, small-group, or whole-class level, while the implementer determines whether it is executed by the AI teacher, the human teacher, or jointly. This distinction connects previously studied problems of classroom organisation and human–AI role allocation [4, 5] without collapsing them into a single decision.

For example, in a class of 25 students, six might make errors across different tasks due to the same gap in negative number operations. The system can suggest small-group support, while the teacher approves or modifies the decision. Following the intervention, all six students are tested individually; if the difficulty persists, subsequent support is chosen. This example is conditional and does not establish fixed intervention thresholds.

Table 1. Examples of intervention level and implementer selection

Educational Data Pattern	Possible Intervention Level	Possible Implementer
Local, low-uncertainty individual gap	Individual	AI
Persistent or context-dependent individual gap	Individual	Teacher or joint human–AI
Common gap among multiple students due to identical causes	Small group	AI teacher, human teacher, or joint human–AI
Widespread prerequisite knowledge gap due to identical causes	Whole class	Primarily teacher or joint human–AI
Gap among many students due to diverse causes or high uncertainty	Teacher discretion—not automatically whole-class	Teacher or joint human–AI

The table presents conceptual examples rather than empirically validated algorithms. Specific rules and thresholds must be determined through subsequent validation. Distinguishing between intervention level and implementer also allows some routine, low-uncertainty individual adaptations to the AI, while increasing teacher involvement in persistent, uncertain, or high pedagogical impact cases.

3.4. Macro-Level and the Closed Multi-Level Coordination Cycle

At the macro-level, the teacher maintains a pivotal role concerning shared goals, classroom progress, and contextual pedagogical judgment [4, 5, 18, 21]. AI can process large-scale educational data and support decisions, but its scope of operation is not synonymous with pedagogical authority. The teacher can organize explanations of general problems, discussions, and group interventions, review AI recommendations, and modify the chosen intervention if necessary.

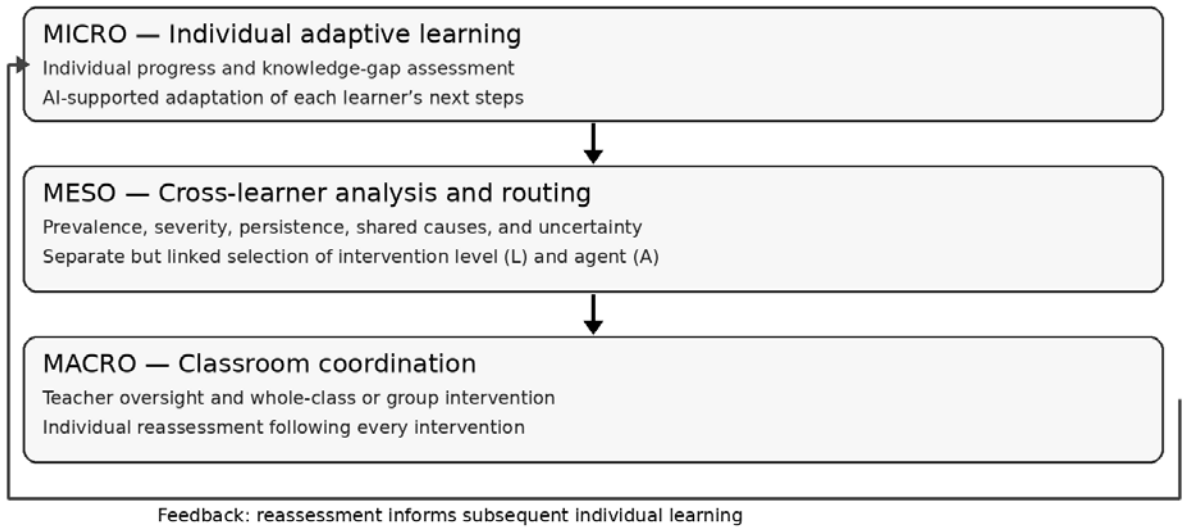
An intervention does not mark the end of the coordination cycle. Following an individual, small-group, or whole-class intervention, each student's knowledge acquisition state must be reassessed, because a general intervention does not imply the exact same outcome for all students.

Post-reassessment, a student may return to the general class flow, continue differentiated support, be transferred to more direct teacher intervention, or receive more advanced tasks.

This process describes the individualized organization of subsequent instruction while accounting for general classroom work; its purpose is not to return all learners to the identical pace, but to coordinate their subsequent learning with the classroom's collective activity. Thus, the system closes the feedback loop, moving from individual data to data aggregation, selection of intervention level and implementer, intervention, and back to individual reassessment. The relationship between the three levels is illustrated in Figure 1.

Adaptation within the framework is implemented across two interconnected levels. In one case, instruction is tailored to the individual student's current state, whereas in the other, aggregating the learning needs of diverse students alters the organization of classroom instruction. Their combination unites individual adaptation with class-level coordination.

Figure 1. The relationship between the three levels



4. Hybrid Class Organization and Human–AI Co-Regulation

In a hybrid class, the human teacher and the AI teacher complement one another, coupling general instruction with individual assessment and adaptation. By aggregating student data, the intervention level and implementer are chosen, and outcomes are reassessed individually following the intervention.

4.1. From General Instruction to Individual Support and Classroom Response

The cycle can begin with the teacher introducing a general goal, problem, or explanation. Subsequent individual checking reveals how each student has grasped the respective content. In case of satisfactory results, the student moves forward, whereas in case of a local gap, the AI—within established bounds—can offer an additional explanation, practice exercise, or hint.

Simultaneously, individual data are aggregated at the meso-level. If the same or a connected gap is observed in multiple students, the intervention can shift to the small-group level, or to the whole-class level in the case of a widespread prerequisite gap. These transitions are not novel concepts in themselves [4, 19, 22]; in the proposed system, their selection is tied to aggregated student data and the choice of intervention level and implementer.

4.2. Dynamic Co-Regulation and Handover to the Human Teacher

In a hybrid classroom, the distribution of functions between the AI teacher and the human teacher can shift depending on student learning needs and the pedagogical judgment required for intervention. Three modes are distinguished [5]. Under AI-driven instruction, the AI chooses tasks within set limits, provides explanations and hints, and checks outcomes. Under teacher-led instruction, the teacher organizes the intervention, while AI supports data presentation and outcome reassessment. Under joint human–AI instruction, the AI can identify difficulties and propose interventions, while the human teacher evaluates and modifies the proposal and organizes execution.

Transitions between modes can occur during the lesson. If difficulties persist after AI interventions, data are insufficient for a confident decision, or the situation requires more sophisticated pedagogical assessment, the system can suggest involving the human teacher. Upon handover, the teacher should receive not only a notification but also the necessary background information: what difficulty was detected, based on what data, what support was already provided, and what outcome was achieved. Handover is an intended mechanism of collaboration, not an obligatory failure of the AI teacher. The framework does not define universal quantitative thresholds for handover; these must be tested in subsequent experimental research.

4.3. Returning Functions to the AI Teacher and Human Oversight

Involving the human teacher does not mean that the student's subsequent learning must permanently involve their direct participation. Once the teacher clarifies or corrects the difficulty, and new learning data show that the student can resume individual adaptive learning, certain functions can be transferred back to the AI teacher. Thus, handover is bidirectional. For instance, the human teacher can determine the cause of a persistent difficulty, provide an explanation, and organize a verification task. Given satisfactory results, the student can proceed with AI support, or receive another intervention if the difficulty persists. This allows focusing teacher attention on situations requiring direct pedagogical participation.

Simultaneously, the AI teacher's operational autonomy must have clear boundaries. It is necessary to pre-define which actions it can execute independently, when human teacher approval is required, and when automated intervention should be suspended or reviewed. The human teacher retains the right to review, modify, or terminate AI recommendations and actions, as well as to change the intervention level or implementer. Thus, the operational autonomy of the AI teacher is combined with the ultimate pedagogical responsibility of the human teacher.

4.4. Individual Reassessment and Subsequent Instruction Organization

During a hybrid class, the outcome of each intervention must be evaluated. Executing an intervention does not mean that the identified learning difficulty has been overcome. Regardless of whether the intervention was conducted at the individual, small-group, or whole-class level, the outcome must be verified for each student individually, since learners may exhibit different mastery levels following a shared instructional event. Knowledge reassessment can be implemented via an appropriate task, brief quiz, or other learning activity. It is crucial to verify the exact knowledge or skill targeted by the intervention; mere participation or a single correct answer is not always sufficient proof of stable mastery.

Based on the results, each student's next step is determined. If the difficulty is overcome with sufficient confidence, the student can continue learning. If it persists, additional support can be provided or another intervention chosen. If higher preparedness is observed, tasks deepening the

knowledge can be offered. The individualized organization of subsequent instruction does not mean returning all students to the same task or pace; it means aligning their individual learning with the classroom's overall work while maintaining differentiated progress.

Each intervention generates new educational data utilized for subsequent decisions. Consequently, instructional organization relies not only on initial assessment but also on the outcomes of implemented interventions. The hybrid class becomes a process of continuous assessment, intervention, and reassessment, where the AI teacher supports individual learning while the human teacher retains overarching pedagogical control and responsibility.

5. Discussion, Limitations, and Empirical Validation

5.1. Position of the Proposed Framework Relative to Existing Research

The proposed framework builds upon research into individual adaptive learning [1, 8–10], learning analytics and teacher decision support [2, 3, 12, 15], classroom transitions [4, 19], and human–AI co-regulation [5, 18, 20, 21].

Previous work bounds the framework's claim to novelty. Yang and co-authors' Pair-Up study (2023) has already explored human–AI co-organisation and transitions between individual and collaborative learning [22], serving as an important precedent close to the proposed framework. The proposed framework aims to differentiate itself through a unified cycle of separate selection of intervention level and implementer, data aggregation, and post-intervention reassessment for each student; the integrity of this differentiation still requires comparative testing. Olsen and co-authors [4] described the joint coordination of social transitions across individual, small-group, and whole-class work. Lawrence and co-authors [5] investigated shared control and transition organization between teachers and AI, while Holstein and co-authors [7] outlined a general framework for human–AI hybrid adaptivity. Therefore, transitions, co-regulation, and hybrid adaptation are not isolated novelties. Various models of human–AI hybrid adaptation, joint classroom coordination, and data-driven instructional interventions exist in the literature. The proposed framework seeks to link them within a unified multi-level decision cycle featuring separate selection of intervention level and implementer alongside post-intervention individual reassessment. Literature selection is targeted and does not represent a systematic or exhaustive search. The exclusivity of this linkage in the literature and its added effectiveness are not yet established; broader comparative approaches and empirical verification are required.

5.2. Limitations of the Framework

The proposed Human–AI Multi-Level Adaptive Learning system is a conceptual model whose practical effectiveness is subject to empirical testing. Its theoretical grounding and structural integrity do not inherently prove that implementing the system will improve student learning outcomes or reduce teacher workload.

The first limitation is the uncertainty in assessing a student's knowledge state. The AI system can analyse student responses, errors, help requests, and task completion trajectories. However, these data do not fully reflect student knowledge. The same error can stem from different causes, and a correct answer does not always indicate stable mastery of the corresponding knowledge. Therefore, it is necessary to differentiate between observed educational data, the knowledge state estimated from them, and the intervention selected based on that estimate.

The second limitation is the unvalidated criteria for intervention selection. The framework proposes accounting for the prevalence, severity, recurrence frequency of learning difficulties,

prerequisite knowledge importance, and estimation uncertainty. However, research is still needed on how these factors should proportionally influence the selection of intervention level and implementer. Without appropriate testing, the confidence score calculated by an AI system cannot be viewed as an unconditional, reliable assessment of a student's knowledge state.

The third limitation is the complexity of classroom coordination. Frequent shifts between individual learning, small-group work, and whole-class interventions can complicate lesson organization. If the system presents the human teacher with an excessive number of recommendations or demands frequent approvals, it may increase rather than decrease their workload [18, 21]. Consequently, the organizational costs of implementing the system must also be evaluated.

The fourth limitation is applicability across diverse learning contexts. The framework may be more easily implemented in topics with clearly defined learning objectives and assessable prior knowledge. In open-ended, creative, investigative, or long-term collaborative tasks, assessment and intervention selection may require alternative approaches.

The fifth limitation encompasses requirements for data protection, student agency, and responsible use [15, 21]. Students should be able to voice their difficulties and understand the support offered to them. Groups must be temporary and revisable to avoid stigmatization. Continuous collection and analysis of student educational data, especially for minors, require privacy, clear usage purposes, access restriction, and human teacher oversight. Assessments concerning students must be grounded in necessary educational data, excluding unfounded psychological or other sensitive profiling. These limitations demonstrate that the framework's effectiveness, reliability, and responsible use conditions must be investigated within real educational environments.

5.3. Empirical Validation Strategy

Validation is appropriately conducted in three phases. First, in the technical and diagnostic phase, the reliability of student state estimation, gap classification, student data aggregation, uncertainty calibration, and guidance recommendations should be evaluated by comparing them against expert pedagogical judgments. Second, in the classroom feasibility phase, the teacher's perception and modification of recommendations, control handovers, group formation applicability, teacher attention demand, and classroom instructional continuity should be examined.

The third phase requires comparative effectiveness evaluation. Three primary conditions are planned: A (standard teaching), B (individual AI adaptation without meso-level coordination), and C (full multi-level human–AI coordination). An additional condition D—guidance via simple threshold rules—will test whether decisions based on aggregated data offer an advantage over simple rules.

- **Condition A:** standard teaching led by a human teacher,
- **Condition B:** student-level AI individualization without meso-level coordination,
- **Condition C:** full multi-level human–AI coordination,
- **Condition D:** the same system with simple threshold guidance (additional comparative condition).

The B–C comparison is pivotal; it will more directly test whether student data aggregation, intervention guidance, individual reassessment, and interconnection create added value compared to student-level AI individualization alone.

Outcomes are appropriately evaluated at three levels. At the student level: mastery, gap overcoming, time required for mastery, and delayed retention. At the teacher level: intervention-related workload, recommendation utilization, and perceived control. At the system/class level: guidance accuracy, frequency of redundant interventions, waiting time, lesson disruptions, and successful interconnection. Immediate correct answers are insufficient proof of long-term retention; thus, individual reassessment must be supplemented by delayed testing.

The value of intervention level and implementer selection must also be compared against simpler rules, such as pre-set thresholds or teacher-selected guidance. The framework must also be falsifiable: its core assumptions would be weakened if data aggregation fails to improve intervention organization, if intervention guidance offers no advantage over simpler rules, if individual reassessment fails to improve post-intervention decisions, or if coordination costs outweigh its supplementary educational value.

Thus, the core question of future empirical work is whether distributed, student-level educational data can be reliably translated into actionable decisions regarding intervention level and implementer while maintaining individual adaptability, meaningful human control, and classroom instructional continuity.

6. Conclusion

The article proposed a Human–AI Multi-Level Adaptive Learning framework to align individual learning with classroom organization.

The framework's distinctive contribution is not the proposal of isolated components, but their linkage within a closed feedback cycle. Student data are aggregated, the intervention level and implementer are separately selected, and following the intervention, each student's outcome is reassessed. Based on new data, their individual learning and, where necessary, classroom work organization are adapted.

The effectiveness of the proposed framework has not yet been confirmed empirically. Future research must test the reliability of data aggregation, the applicability of intervention guidance and human–AI control handovers, as well as the impact of reassessment and interconnection. The pivotal question is whether multi-level coordination possesses measurable added value compared to individual AI tutoring alone.

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