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## IMPLEMENTING AI-BASED PERSONALIZED LEARNING IN MIDDLE-SCHOOL INFORMATICS: A HYBRID INSTRUCTIONAL MODEL

### *Abstract*

This article examines the integration of artificial intelligence-based adaptive learning systems with traditional pedagogical approaches in middle-school informatics education. The study aims to develop a hybrid instructional framework for supporting personalized learning trajectories, with particular emphasis on low-achieving students. The research is based on a systematic synthesis of selected Scopus- and Web of Science-indexed studies published between 2017 and 2025. Using conceptual modelling and thematic analysis, the study identifies key technological, pedagogical, cognitive, and motivational factors influencing personalized learning in informatics. On this basis, a three-layer hybrid framework is proposed, integrating AI-driven diagnostics and adaptivity, teacher-led instructional mediation, and learner-centered personalized trajectories. The model also incorporates a four-stage learning cycle consisting of diagnostic assessment, pathway design, hybrid instruction, and mastery validation. The results demonstrate that hybrid human-AI instructional models enhance learning outcomes by reducing cognitive overload, providing immediate feedback, supporting self-regulation, and strengthening learner motivation. Low-achieving students benefit from individualized task progression and sustained pedagogical support, while teachers gain access to data-informed instructional tools that facilitate targeted intervention. The study highlights the importance of ethical governance, teacher professional development, and infrastructural readiness for successful implementation of adaptive technologies. Although the proposed framework is conceptual, it provides a theoretically grounded foundation for future empirical research and practical innovation in informatics education.

**Keywords:** artificial intelligence in education, personalized learning, adaptive learning systems, informatics education, hybrid pedagogy, low-achieving students, differentiated instruction, learning analytics.

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## ВНЕДРЕНИЕ ПЕРСОНАЛИЗИРОВАННОГО ОБУЧЕНИЯ НА ОСНОВЕ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА В ПРЕПОДАВАНИЕ ИНФОРМАТИКИ В ОСНОВНОЙ ШКОЛЕ: ГИБРИДНАЯ УЧЕБНАЯ МОДЕЛЬ

### *Аннотация*

В статье рассматривается интеграция адаптивных систем обучения на основе искусственного интеллекта с традиционными педагогическими подходами в обучение информатике в основной школе. Цель исследования – разработка гибридной учебной модели для поддержки персонализированных образовательных траекторий с особым акцентом на обучающихся с низкой учебной успеваемостью. Исследование основано на систематическом анализе научных публикаций, индексируемых в базах Scopus и Web of Science за период 2017–2025 гг. С использованием методов концептуального моделирования и тематического анализа в работе выявлены ключевые технологические, педагогические, когнитивные и мотивационные факторы, влияющие на персонализированное обучение информатике. На этой основе предложена трёхуровневая гибридная модель, интегрирующая AI-диагностику и адаптивность, педагогическое сопровождение со стороны учителя и ориентированные на обучающегося образовательные траектории. Модель также включает четырёхэтапный цикл обучения, состоящий из диагностической оценки, проектирования индивидуального маршрута, гибридного обучения и подтверждения уровня освоения материала.

Результаты исследования показывают, что гибридные модели «человек-искусственный интеллект» способствуют повышению учебных достижений за счёт снижения когнитивной нагрузки, обеспечения

оперативной обратной связи, развития саморегуляции и усиления учебной мотивации. Обучающиеся с низкой успеваемостью получают преимущества в виде индивидуализированного темпа обучения и устойчивой педагогической поддержки, а педагоги – доступ к инструментам аналитики для реализации адресных образовательных интервенций. В статье подчёркивается значение этического регулирования, профессиональной подготовки педагогов и развитой инфраструктуры для успешного внедрения адаптивных технологий. Несмотря на концептуальный характер исследования, предложенная модель формирует теоретически обоснованную основу для дальнейших эмпирических исследований и практических инноваций в области обучения информатике.

**Ключевые слова:** искусственный интеллект в образовании, персонализированное обучение, адаптивные системы обучения, обучение информатике, гибридная педагогика, обучающиеся с низкой успеваемостью, дифференцированное обучение, образовательная аналитика.

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## НЕГІЗГІ МЕКТЕПТЕ ИНФОРМАТИКАНЫ ОҚЫТУДА ЖАСАНДЫ ИНТЕЛЛЕКТКЕ НЕГІЗДЕЛГЕН ДЕРБЕСТЕНДІРІЛГЕН ОҚЫТУДЫ ЕНГІЗУ: ГИБРИДТІ ОҚУ МОДЕЛІ

### *Аңдатпа*

Мақалада негізгі мектепте информатиканы оқытуда жасанды интеллектке негізделген бейімделген оқыту жүйелерін дәстүрлі педагогикалық тәсілдермен ықпалдастыру мәселелері қарастырылады. Зерттеудің мақсаты — білім алушылардың жеке оқу траекторияларын қолдауға арналған гибриді оқу моделін әзірлеу, әсіресе оқу үлгерімі төмен оқушыларға баса назар аудару. Зерттеу 2017–2025 жылдар аралығында Scopus және Web of Science дерекқорларында индекстелген ғылыми еңбектерді жүйелі талдауға негізделген. Концептуалдық модельдеу мен тақырыптық талдау әдістерін қолдану арқылы информатиканы дербестендіріп оқытуға әсер ететін негізгі технологиялық, педагогикалық, когнитивтік және мотивациялық факторлар анықталды. Осы негізде AI-диагностикасы мен бейімделу тетіктерін, мұғалімнің педагогикалық қолдауын және білім алушыға бағытталған оқу траекторияларын біріктіретін үш деңгейлі гибриді модель ұсынылды. Модель диагностикалық бағалау, жеке оқу жолын жобалау, гибриді оқыту және меңгеру деңгейін растау кезеңдерінен тұратын төрт сатылы оқу циклін қамтиды. Зерттеу нәтижелері «адам–жасанды интеллект» гибриді модельдерінің когнитивтік жүктемені азайту, жедел кері байланыс ұсыну, өзін-өзі реттеу дағдыларын дамыту және оқу мотивациясын арттыру арқылы оқу жетістіктерін жақсартатынын көрсетеді. Оқу үлгерімі төмен білім алушылар жеке қарқынмен оқуға және тұрақты педагогикалық қолдауға қол жеткізеді, ал мұғалімдер мақсатты білім беру интервенцияларын жүзеге асыруға мүмкіндік беретін аналитикалық құралдарды пайдалана алады. Мақалада бейімделген технологияларды табысты енгізу үшін этикалық реттеудің, педагогтердің кәсіби даярлығының және инфрақұрылымдық қамтамасыз етудің маңыздылығы атап өтіледі. Зерттеу концептуалдық сипатта болғанымен, ұсынылған модель информатиканы оқыту саласындағы болашақ эмпирикалық зерттеулер мен практикалық инновациялар үшін теориялық негіз қалыптастырады.

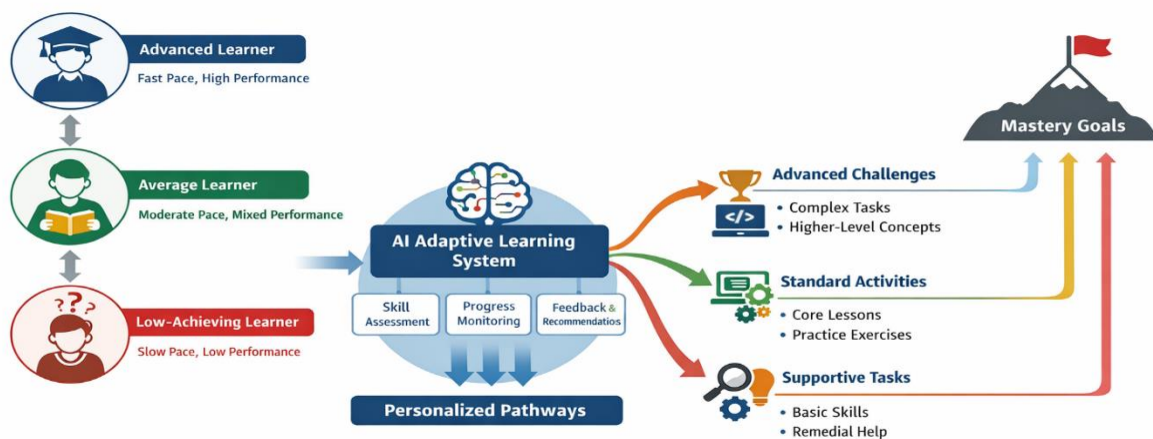
**Түйін сөздер:** білім берудегі жасанды интеллект, дербестендірілген оқыту, бейімделген оқыту жүйелері, информатиканы оқыту, гибриді педагогика, оқу үлгерімі төмен білім алушылар, саралап оқыту, білім беру аналитикасы.

### **Introduction**

Informatics education occupies a central position in modern school curricula, serving not only as an independent academic discipline but also as a foundational component for the development of digital literacy, algorithmic thinking, and computational problem-solving skills. For students in grades 5–9, informatics represents the first systematic encounter with abstract concepts, formal logic, and structured methods of solving complex tasks. At this stage, learners are required to master fundamental processes such as decomposition, pattern recognition, debugging, and logical reasoning, which form the basis for further learning in science, technology, engineering, and mathematics. Despite the increasing importance of informatics in contemporary education, a significant number of middle-school students demonstrate persistent learning difficulties in this subject. Low-achieving learners frequently experience challenges in understanding abstract programming concepts, applying

algorithmic structures, transferring knowledge between tasks, and sustaining motivation during prolonged learning activities. Empirical studies indicate that traditional instructional approaches, primarily based on teacher explanations, standardized exercises, and uniform assessment procedures, are often insufficient for addressing the diverse cognitive and motivational needs of such students [1; 2; 3]. In recent decades, educational systems worldwide have increasingly shifted toward personalized learning models, recognizing that standardized instructional frameworks cannot adequately accommodate individual differences in prior knowledge, learning pace, cognitive style, and readiness. Personalized learning pathways are understood as structured and flexible sequences of educational experiences that are adapted to the learner’s individual characteristics and developmental trajectory [4; 5]. This pedagogical shift has been strongly supported by advances in artificial intelligence technologies, which enable large-scale analysis of student data and dynamic adaptation of instructional content [1; 6].

As shown in Figure 1, an AI Adaptive Learning System enables personalized instruction in informatics by assessing skills, monitoring progress, and providing targeted feedback. Based on diagnostic data, students follow differentiated pathways—advanced challenges, standard activities, or supportive tasks—while all trajectories lead toward common mastery goals. This approach ensures alignment between learner needs and cognitive demands, promoting both equity and academic progress in heterogeneous classrooms.



Personalized Learning Pathways in Informatics Education

Figure 1. Conceptual diagram of personalized learning pathways in informatics education, illustrating adaptation to learner pace, readiness, and performance

AI-powered adaptive learning platforms are capable of collecting, processing, and interpreting diverse forms of learner data, including interaction records, performance indicators, error patterns, and time-on-task measures. Based on these data, such systems construct dynamic learner models and generate personalized recommendations for further learning activities [1; 6; 7]. In informatics education, where student performance is reflected in code submissions, debugging processes, and algorithmic solutions, these technologies allow for highly precise and fine-grained personalization [8]. However, despite rapid technological progress, instructional practice in many middle-school informatics classrooms continues to rely predominantly on traditional pedagogical methods. Teacher-centered explanations, guided practice, and standardized assessments remain the dominant forms of instruction. Although these approaches play an important role in developing conceptual understanding and maintaining classroom organization, they often fail to provide sufficient differentiation for students with systematic learning difficulties. As a result, low-achieving learners frequently accumulate learning gaps, experience reduced academic self-efficacy, and demonstrate declining engagement.

Recent research emphasizes that the most effective instructional models are hybrid in nature, integrating AI-driven adaptivity with human-centered pedagogy [9; 10; 11]. In such models, artificial intelligence supports instruction through real-time diagnostics, personalized feedback, and adaptive task sequencing, while teachers provide conceptual explanations, motivational guidance, and socio-emotional support. As illustrated in Figure 2, this three-layer hybrid instructional model integrates AI systems, teacher pedagogy, and learner experience into a coherent framework, ensuring continuous feedback loops between diagnostics, instructional interventions, and student progress.

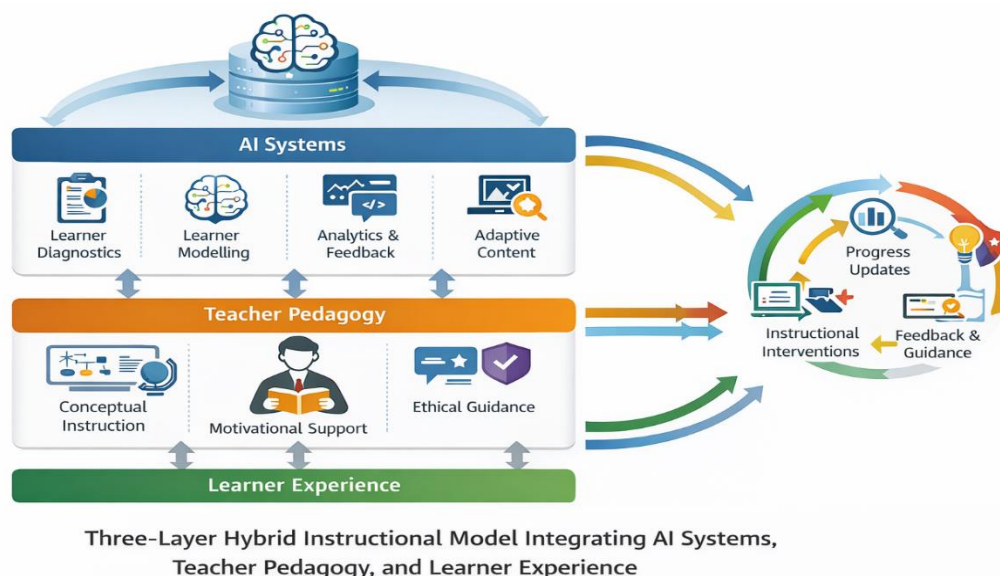


Figure 2. Three-layer hybrid instructional model integrating AI systems, teacher pedagogy, and learner experience

For low-achieving students, hybrid instructional models offer substantial pedagogical advantages. AI systems ensure continuous monitoring of learning progress and immediate corrective feedback, while teachers address misconceptions, foster self-regulation, and support learners' motivation [12; 13; 14].

Within the context of this study, personalized learning trajectories are conceptualized as dynamic and iterative pathways that integrate diagnostic assessment, adaptive content delivery, teacher-mediated instruction, and reflective practice. These trajectories are continuously updated based on learner performance and instructional feedback.

Against this background, the present study addresses an important research gap by synthesizing contemporary scientific evidence and proposing a comprehensive framework for implementing AI-supported personalized learning trajectories in middle-school informatics education. Drawing on selected high-impact studies indexed in Scopus and Web of Science, the article develops a conceptual hybrid model and outlines its pedagogical implications for supporting low-achieving learners.

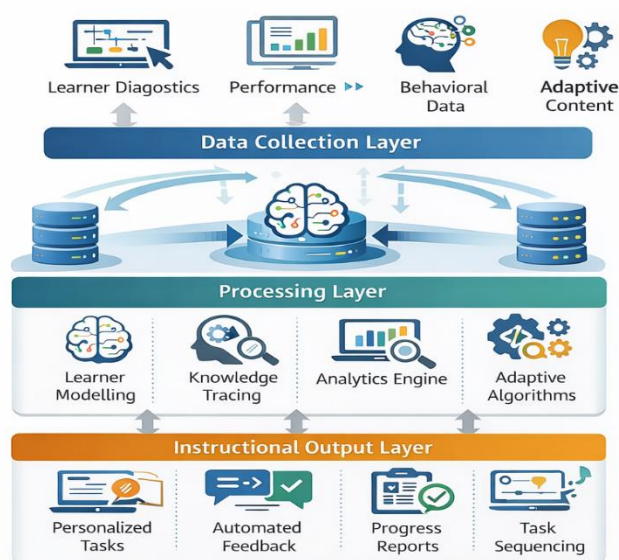
The main objective of this study is to analyze current research on AI-powered adaptive learning systems, personalized learning frameworks, and differentiated instruction in informatics education and to integrate these findings into a unified instructional model. The novelty of the research lies in presenting a synthesized, domain-specific framework that combines technological, pedagogical, and cognitive dimensions within middle-school informatics.

An analysis of the works of foreign and domestic researchers has shown that issues of personalized learning, adaptive educational systems, and the integration of artificial intelligence into the instructional process occupy a significant place in contemporary pedagogical theory and practice.

Contemporary educational research demonstrates that artificial intelligence has become one of the most influential technological factors shaping modern digital learning environments. AI-based

systems enable fine-grained adaptivity and large-scale personalization of instruction through continuous analysis of learner data and automated instructional decision-making processes. Numerous studies emphasize that well-designed adaptive systems are capable of modelling student knowledge, detecting misconceptions, dynamically adjusting task difficulty, and recommending individualized learning pathways based on evolving performance indicators [1; 2; 6]. As illustrated in Figure 3, the architecture of AI-powered adaptive learning systems typically consists of interconnected data collection, processing, and instructional output layers that work together to support personalized instruction.

At the core of AI-powered adaptive learning environments lies the concept of dynamic learner modelling. Such models integrate data related to learners' interaction patterns, response accuracy, error frequency, time-on-task, and behavioural indicators into unified representations of student competence. These representations allow intelligent tutoring systems and adaptive learning platforms to implement knowledge-tracing mechanisms and predictive analytics that identify latent learning gaps.



Architecture of AI-Powered Adaptive Learning Systems

Figure 3. Architecture of AI-powered adaptive learning systems: data collection, processing, and instructional output layers

Informatics education represents a particularly favourable domain for the application of AI adaptivity. Programming activities, debugging procedures, and algorithmic problem-solving tasks generate structured digital traces that can be efficiently processed by adaptive systems [8; 15]. Research indicates that these data streams enable precise personalization of instructional content and facilitate early detection of learning difficulties in computational thinking and coding skills.

A central advantage of AI-based learning environments is the provision of immediate and personalized feedback. Unlike traditional assessment mechanisms, which often involve significant time delays, adaptive platforms generate corrective hints and explanatory messages in real time. This immediacy supports error correction, sustains learner engagement, and reduces frustration associated with prolonged uncertainty [4; 6]. Empirical investigations and meta-analytical studies consistently confirm the positive impact of adaptive technologies on academic achievement. Hu [12] reports moderate to strong effect sizes across STEM disciplines, including computer science, while Yaseen [7] demonstrates that learners with lower baseline skills experience disproportionately strong benefits. These findings suggest that AI-based personalization contributes to reducing educational inequality. However, personalization in education extends beyond algorithmic adaptivity and

encompasses broader pedagogical and psychological dimensions. Effective personalization aligns instruction with learner identity, interests, motivation, and metacognitive capabilities [4; 10]. Consequently, personalized learning should be understood as an integrated pedagogical strategy rather than a purely technological feature. In informatics education, personalization is particularly important due to the cognitive demands associated with abstract concepts, syntactic structures, and multi-layered algorithms. Studies demonstrate that learners differ substantially in their pace of mastering variables, loops, conditional statements, and recursion, leading to divergent learning trajectories if uniform instruction is applied [8; 16].

Middle-school students represent a transitional cognitive group characterized by uneven development of abstract reasoning and self-regulation abilities. Research indicates that personalized technologies are especially effective for learners in grades 6–9, as they support gradual transitions from concrete to abstract thinking and provide structured scaffolding [17]. Low-achieving students in informatics frequently exhibit limitations in working memory, abstraction, and metacognitive monitoring. These constraints impair the ability to follow multi-step algorithms and sustain engagement in complex programming tasks [14; 18]. Without timely support, such learners often enter cycles of repeated failure and disengagement. Traditional pedagogical approaches have attempted to address these challenges through guided practice, task segmentation, and explicit modelling of problem-solving strategies [3; 19]. However, empirical evidence suggests that these methods are insufficient without continuous differentiation and monitoring [17].

Technology-enhanced differentiation offers scalable solutions by automatically adjusting task difficulty, providing multimodal representations, and enabling unlimited practice opportunities. Learning analytics dashboards allow teachers to target interventions more efficiently by identifying learners who require additional support [14; 20].

Despite technological advances, the literature consistently emphasizes that teachers remain central to effective personalized learning. Human instructors provide motivational scaffolding, emotional support, conceptual clarification, and ethical oversight. Hybrid instructional models that integrate AI systems with teacher-led pedagogy demonstrate superior learning outcomes [9; 10; 11]. Implementation challenges remain, including limited AI literacy among teachers, infrastructural constraints, and ethical concerns related to data privacy. Addressing these barriers is essential for sustainable adoption of hybrid models. Overall, the literature demonstrates strong convergence on the effectiveness of AI-enhanced personalization, the importance of teacher mediation, and the suitability of informatics education for adaptive technologies. This synthesis provides a robust theoretical foundation for the hybrid framework proposed in this study.

### **Research methodology**

This study employs a conceptual and analytical research design aimed at synthesizing contemporary scientific evidence and developing an integrated hybrid framework for personalized learning trajectories in middle-school informatics education. Given the theoretical orientation of the research, primary empirical data collection was not conducted. Instead, the methodology is grounded in systematic literature analysis, design-based reasoning, and conceptual educational modelling, which are widely applied in studies seeking to integrate technological, pedagogical, and cognitive perspectives [4; 9]. The research design follows the principles of design-based educational research and conceptual synthesis. These approaches emphasize iterative development of theoretical models based on accumulated empirical findings and continuous alignment with pedagogical theory. The analytical process involved identifying persistent learning difficulties among low-achieving informatics students, aggregating evidence from high-impact academic sources, extracting recurring instructional and technological patterns, and constructing a hybrid framework aligned with established personalization theories [1; 12].

The empirical foundation of the study consists of thirty peer-reviewed publications indexed in Scopus and Web of Science and published between 2017 and 2025. The selection process prioritized studies addressing artificial intelligence in education, adaptive learning systems, personalized

instruction, informatics education, and differentiated pedagogical support. Publications focused exclusively on higher education, non-peer-reviewed materials, or non-instructional applications of AI were excluded to ensure contextual relevance and methodological rigor.

Data analysis was conducted through a multi-stage qualitative synthesis procedure. In the first stage, each publication was examined using thematic coding to identify core constructs related to adaptive technologies, feedback mechanisms, learning challenges, personalization strategies, and hybrid pedagogy. Codes were derived inductively and refined through iterative comparison across sources to ensure conceptual consistency.

In the second stage, thematic codes were grouped into broader analytical categories representing technological, pedagogical, cognitive, motivational, and environmental dimensions of learning. Technological factors included adaptive engines, analytics systems, and knowledge-tracing algorithms. Pedagogical factors encompassed instructional design, scaffolding practices, and teacher mediation. Cognitive factors reflected learners' prior knowledge, misconceptions, and working memory limitations. Motivational factors included engagement, self-efficacy, and self-regulation. Environmental factors addressed infrastructure availability and teacher preparedness.

In the third stage, integrative synthesis was performed using cross-matrix analysis. This technique enabled systematic mapping of pedagogical challenges to technological and human intervention strategies. The matrix identified instructional functions best addressed by AI systems, those requiring teacher mediation, and those benefiting from collaborative human–AI intervention. As illustrated in Figure 4, this Human–AI Division of Pedagogical Labor Matrix visually represents the distribution of diagnostic, monitoring, feedback, and adaptivity functions between AI systems and human teachers, thereby operationalizing the hybrid instructional framework. This analysis formed the basis for defining optimal division of pedagogical labor within the hybrid model.

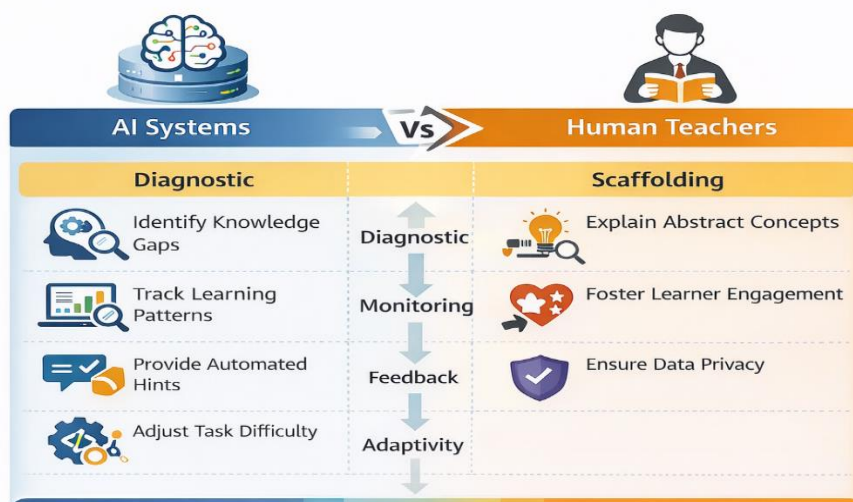


Figure 4. Human–AI division of pedagogical labor matrix

Conceptual modelling methods were employed to translate analytical findings into a coherent instructional framework. The proposed hybrid model is structured according to a layered architecture reflecting interactions among AI systems, pedagogical practices, and learner experiences. Dynamic flow modelling techniques were applied to visualize information exchange among diagnostic modules, instructional processes, and feedback loops.

Actor-function mapping was used to define the responsibilities of key participants in the instructional process. AI systems were assigned functions related to monitoring, analytics, and automated feedback. Teachers were responsible for conceptual guidance, motivation, and ethical oversight. Learners were positioned as active agents responsible for engagement and reflection. This mapping ensures balanced integration of technological and human contributions.

Ethical and pedagogical principles were embedded within the methodological framework. Data privacy, algorithmic fairness, transparency, and teacher autonomy were prioritized in accordance with international guidelines [11]. Pedagogically, the framework emphasizes prevention of cognitive overload, avoidance of learner isolation, and systematic professional development.

Validity of the conceptual model was ensured through triangulation across multiple theoretical and empirical domains, including personalized learning theory, adaptive system research, informatics education studies, and hybrid pedagogy frameworks [9; 12;]. Reliability was supported through consistent application of thematic coding procedures and cross-verification of conceptual categories.

Several methodological limitations must be acknowledged. The absence of primary empirical data restricts direct evaluation of classroom effectiveness. Variability in study quality and contextual differences may affect generalizability. Rapid evolution of AI technologies may require periodic model revision.

Despite these limitations, conceptual modelling provides a necessary foundation for subsequent empirical research. The methodology establishes a systematic basis for experimental validation and longitudinal investigation of hybrid personalized learning trajectories.

### **Results of the study**

This section presents the results of the conceptual synthesis conducted on the basis of selected Scopus- and Web of Science-indexed studies. The analysis integrates technological, pedagogical, cognitive, and motivational dimensions of personalized learning in informatics education. The principal outcome is the development of a hybrid instructional framework that combines artificial intelligence-driven adaptivity with teacher-led pedagogy to support individualized learning trajectories, particularly for low-achieving students.

The proposed model is designed as a dynamic multi-layered system in which artificial intelligence and human instruction function in complementary roles. The framework responds to learners' cognitive readiness, motivational states, and developmental needs while maintaining alignment with curriculum standards.

At the core of the model lies a three-layer architecture representing interactions among technological systems, pedagogical practices, and learner experiences. The first layer, the AI adaptive engine, encompasses diagnostic modules, learner modelling algorithms, analytics tools, feedback generators, and task sequencing mechanisms. This layer continuously processes learner data to identify mastery patterns, misconceptions, and engagement trends [1; 6; 12].

The second layer represents teacher-led pedagogical processes, including conceptual instruction, scaffolding strategies, classroom interaction, motivational support, and ethical supervision. Teachers interpret AI-generated analytics and design targeted interventions for learners requiring additional support [9].

The third layer reflects the learner experience and personalized trajectory. It includes engagement with adaptive tasks, progression through competency-based milestones, and reflective activities that promote self-regulation.

One of the central results of the synthesis is the identification of an optimal division of pedagogical responsibilities between artificial intelligence and human teachers. AI systems demonstrate high effectiveness in continuous performance monitoring, pattern detection, automated feedback provision, difficulty adaptation, and learning outcome prediction [2; 7; 13]. These functions enable scalable micro-level personalization in heterogeneous classrooms.

Teachers, in contrast, demonstrate comparative advantages in explaining abstract informatics concepts, scaffolding metacognitive processes, supporting learner motivation, and managing classroom dynamics [17; 19;]. Furthermore, teachers play a crucial role in contextualizing learning analytics and ensuring pedagogical relevance.

The synthesis further reveals a recurring four-stage structure underlying effective personalized learning trajectories. These stages form a cyclical process that integrates diagnostic assessment, instructional design, adaptive practice, and reflective evaluation. As illustrated in Figure 5, this

cyclical four-stage personalized learning trajectory model visually represents the dynamic interaction between diagnostic assessment, pathway design, hybrid instruction, and mastery validation within an iterative developmental loop.

The first stage involves diagnostic foundation, during which AI systems conduct adaptive assessments to determine learners' initial mastery levels and error patterns, while teachers collect contextual and motivational information. The combined output is a comprehensive learner profile.

The second stage focuses on personalized pathway design. AI systems generate recommended task sequences, while teachers refine these pathways in accordance with curricular and pedagogical objectives.

The third stage consists of hybrid instruction and adaptive practice. Teacher-led explanations are combined with individualized work on adaptive platforms, supported by real-time feedback and dynamic difficulty adjustment.

The fourth stage emphasizes mastery validation and reflective practice. AI systems administer adaptive assessments, teachers evaluate conceptual understanding, and students engage in guided reflection.

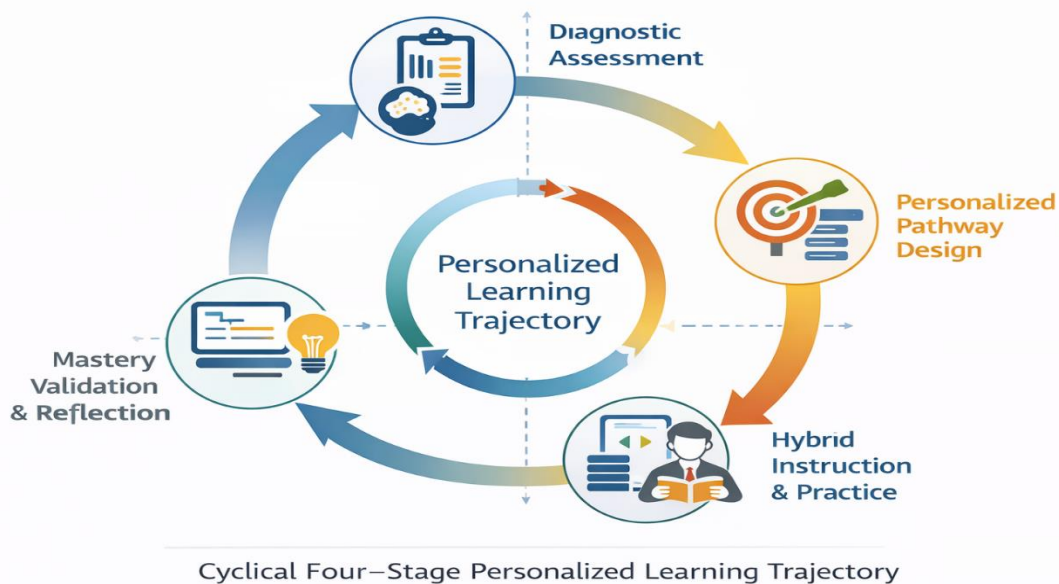


Figure 5. Cyclical four-stage personalized learning trajectory model

An evidence-mapping procedure was conducted to establish theoretical grounding for the proposed framework. This mapping links adaptive programming research [13; 21], personalization meta-analyses [5], differentiation studies [14; 22], and hybrid pedagogy frameworks to specific model components. The convergence of evidence enhances the theoretical reliability of the framework.

Evaluation of projected instructional impact indicates significant benefits for low-achieving learners. The hybrid model reduces cognitive overload through gradual task progression, minimizes error-related frustration through immediate feedback, and strengthens academic self-efficacy through visible mastery milestones. These effects contribute to increased persistence, conceptual understanding, and learner autonomy.

From the teacher's perspective, the framework reduces workload associated with routine assessment and manual differentiation. Automated analytics facilitate early identification of learning difficulties and support data-informed instructional decision-making. Consequently, teachers can focus on individualized coaching and instructional design.

At the classroom level, implementation of the hybrid model promotes inclusive, differentiated, and learner-centered instructional environments. Differentiation becomes systematic, feedback becomes continuous, and instructional processes become more transparent.

Overall, the results demonstrate that hybrid AI–traditional instructional models provide a coherent and theoretically grounded approach to personalized informatics education. The integration of technological precision with human pedagogical expertise establishes conditions for sustainable improvement of learning outcomes.

### **Discussion**

The present study aimed to synthesize contemporary research on artificial intelligence–based adaptive learning systems, personalized instructional frameworks, and differentiated pedagogical practices in order to construct a hybrid model for personalized learning trajectories in middle-school informatics education. The results demonstrate that systematic integration of AI-powered technologies with teacher-led pedagogy creates a balanced instructional environment capable of addressing the diverse cognitive and motivational needs of learners, particularly those exhibiting persistent academic underachievement.

The findings confirm the complementary nature of human and artificial intelligence in educational contexts. AI systems demonstrate strong capacity for micro-level instructional management through continuous monitoring, automated detection of misconceptions, real-time difficulty adjustment, and predictive analytics [1; 7; 12]. These functions enhance instructional responsiveness and enable scalable personalization. Teachers, in contrast, provide essential human elements, including conceptual clarification, motivational scaffolding, socio-emotional support, and ethical oversight [9]. This synergy supports the view of AI as a pedagogical partner rather than a replacement for educators.

The hybrid framework aligns with contemporary theories of learner-centered and mastery-oriented instruction. By delegating routine analytical and assessment tasks to AI systems, teachers are able to focus on higher-order instructional activities, such as facilitating deep conceptual understanding, fostering metacognitive awareness, and supporting learner identity development. This redistribution of instructional labor enhances pedagogical effectiveness and professional autonomy.

One of the most significant implications of the model lies in its potential to promote educational equity. Low-achieving learners are disproportionately affected by delayed feedback, insufficient differentiation, and limited opportunities for mastery. Adaptive learning systems mitigate these disadvantages by providing individualized pathways and continuous formative assessment [12; 13; 14]. In informatics education, where cognitive load increases rapidly due to algorithmic complexity, personalized trajectories enable students to progress at developmentally appropriate rates, thereby reducing frustration and disengagement.

The results also indicate a substantial pedagogical transformation in informatics education. Traditional approaches based on uniform instruction and standardized assessment are increasingly replaced by competency-based progression, adaptive feedback mechanisms, and individualized task sequencing. This transformation aligns with global trends toward digital pedagogy and data-informed teaching practices [8; 16; 21].

From a practical perspective, the hybrid model offers multiple advantages for teachers. Learning analytics enable early identification of conceptual gaps and facilitate targeted interventions. Automated assessment reduces time devoted to routine grading, allowing greater focus on instructional design and individualized coaching. Moreover, systematic use of data supports reflective teaching practices and continuous professional growth.

Low-achieving students benefit from multi-dimensional support embedded within the framework. Gradual task progression reduces cognitive overload, immediate feedback enhances motivation, and teacher-mediated guidance fosters deeper understanding. The interaction of these factors promotes development of self-regulated learning skills, which are essential for sustained success in informatics.

At the institutional level, the model provides administrators with a strategic framework for digital transformation. Integration of adaptive platforms supports systematic monitoring of academic progress, informs professional development planning, and aligns instructional practices with inclusive education policies.

Despite its advantages, several implementation challenges remain. Technological infrastructure limitations, insufficient technical support, and unequal access to devices may constrain consistent platform usage. Teacher readiness represents another critical factor, as many educators lack formal training in AI literacy and data interpretation [23]. Comprehensive professional development programs are therefore essential. Ethical and privacy issues require continuous attention. Adaptive platforms collect sensitive learner data, raising concerns related to security, transparency, and algorithmic bias. The hybrid framework emphasizes teacher mediation and institutional regulation as safeguards against misuse of educational data. Another potential risk involves over-reliance on automated feedback. While AI systems effectively support procedural accuracy, excessive dependence may limit development of critical thinking and conceptual reasoning. Teachers must therefore balance technological support with dialogic and reflective instruction.

Several limitations of the present study must be acknowledged. As a conceptual synthesis, the research lacks primary empirical validation in classroom settings. Differences in national curricula, technological infrastructure, and institutional cultures may affect generalizability. Rapid technological development may also necessitate periodic revision of model components.

These limitations indicate important directions for future research, including experimental validation of hybrid models, longitudinal investigation of learner development, and evaluation of teacher professional development programs. Further studies should also explore integration of generative AI tools for debugging support and metacognitive guidance.

Overall, the discussion demonstrates that hybrid human–AI instructional models represent a viable and theoretically grounded approach to modernizing informatics education. When supported by institutional policy, professional training, and ethical governance, such models can enhance learning quality, promote equity, and foster sustainable pedagogical innovation.

## **Conclusion**

This study developed a comprehensive hybrid instructional framework that integrates artificial intelligence–driven adaptivity with teacher-led pedagogy to support personalized learning trajectories in middle-school informatics education. Through systematic synthesis of selected Scopus- and Web of Science-indexed studies, the research demonstrates that neither purely technological solutions nor exclusively traditional instructional approaches are sufficient to address the diverse cognitive, motivational, and developmental needs of contemporary learners, particularly those exhibiting persistent academic underachievement.

The findings indicate that AI-based adaptive systems provide substantial pedagogical value through continuous learner modelling, real-time feedback, dynamic task sequencing, and predictive analytics. These functions enable micro-level personalization, reduce cognitive overload, and facilitate mastery-oriented progression. At the same time, teachers remain central to effective instruction by delivering conceptual explanations, socio-emotional support, motivational guidance, and ethical supervision. The integration of these complementary strengths forms the foundation of a balanced and sustainable personalized learning environment.

The proposed four-stage personalized learning trajectory, encompassing diagnostic assessment, pathway design, hybrid instruction, and mastery validation, ensures continuous instructional responsiveness and individualized pacing. Through iterative cycles of assessment, adaptation, and reflection, learners receive targeted support aligned with their evolving competencies. This structure promotes autonomy, persistence, and self-regulation, which are essential for long-term success in informatics education. For low-achieving students, the hybrid framework offers an effective mechanism for overcoming learning barriers associated with abstraction, syntax complexity, and problem-solving demands. Immediate feedback reduces error-related frustration, adaptive task progression enhances academic confidence, and teacher-mediated guidance fosters deeper conceptual understanding. As a result, learners are more likely to sustain engagement and develop positive academic self-concepts.

From the perspective of educators, the model reduces workload associated with routine assessment and differentiation while strengthening data-informed instructional decision-making. Teachers are empowered to focus on meaningful pedagogical interactions, individualized coaching, and professional reflection. At the institutional level, the framework supports strategic digital transformation and promotes inclusive education policies.

Despite these advantages, successful implementation requires careful attention to infrastructural readiness, teacher professional development, and ethical governance of educational data. Schools must ensure adequate technological resources, provide sustained training in AI literacy, and establish transparent policies regarding data security and algorithmic accountability.

As a conceptual study, the present research provides a theoretical foundation for subsequent empirical validation. Future investigations should evaluate the effectiveness of hybrid personalized learning trajectories in real classroom settings, examine long-term developmental outcomes, and explore the pedagogical integration of emerging generative AI tools for debugging support, code explanation, and metacognitive guidance.

In conclusion, hybrid integration of artificial intelligence and human pedagogy represents a promising pathway for advancing personalized learning in middle-school informatics. By combining technological precision with professional judgment and ethical responsibility, the proposed model offers a robust approach to enhancing learning quality, promoting educational equity, and preparing students for participation in an increasingly digital society.

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