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An ILM-Grounded Adaptive Framework for Gifted Learners: Integrating LLM Orchestration and Multi-Agent Tutoring

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Abstract: Gifted learners require instructional environments that transcend conventional pedagogical boundaries, offering adaptive challenge, metacognitive scaffolding, and high degrees of learner autonomy. This study presents the design, implementation, and empirical evaluation of the AI-Enhanced Self-Directed Learning (AESDL) framework an integrated adaptive system grounded in Treffinger's Independent Learner Model (ILM) and operationalized through an ensemble of five artificial intelligence (AI) technologies: the Google Gemini API (as central orchestration controller), cognitive computing, multi-agent systems (MAS), expert systems, and automatic speech recognition. The model is built upon four core ILM components Guidance, Self-Development, Enrichment, and Seminars/In-Depth Study each computationally instantiated through dedicated AI subsystems. A quasi-experimental pre-test/post-test control group design was employed with 50 gifted secondary school learners (25 experimental, 25 control) drawn from model gifted-education classrooms in Khartoum State, Sudan. The experimental group received eight weeks of instruction via the AESDL system; the control group received equivalent instruction through conventional electronic resources. Outcome measures self-directed learning skills, problem-solving capacity, and academic enrichment achievement (each scored on a 50-point scale) were analyzed using independent-samples t-tests with Cohen's d effect sizes. Results indicated statistically significant and practically large superiority of the AESDL condition: self-directed learning ($t(48) = 7.91$, $p < .001$, $d = 2.24$), problem-solving ($t(48) = 5.52$, $p < .001$, $d = 1.56$), and academic achievement ($t(48) = 6.50$, $p < .001$, $d = 1.84$). These findings advance the empirical evidence base for AI-mediated gifted education and provide actionable design principles for intelligent adaptive learning systems. The control condition comprised conventional electronic learning resources (digital textbooks, instructional videos, and static online exercises). Ninety-five-percent confidence intervals for the between-group mean differences were [9.13, 15.35], [5.62, 12.06], and [7.02, 13.30] for self-directed learning, problem-solving, and academic achievement, respectively. Given the modest sample ($n = 50$) and the near-ceiling experimental-group scores, these findings should be interpreted with caution regarding potential ceiling effects and limited external validity, and warrant independent replication with larger, more diverse samples.

Index Terms: Cognitive Computing, Gemini API, Large Language Models in Education, Intelligent Agents, Self-Directed Learning, Gifted Education, Independent Learner Model, Adaptive Learning Systems

1. Introduction

The rapid advancement of artificial intelligence (AI) and its increasing integration into educational contexts have fundamentally transformed the landscape of teaching and learning worldwide [1]. AI-driven educational systems offer notable capabilities for personalization, adaptive content delivery, and real-time learner feedback capabilities that are reshaping how institutions conceptualize and deliver instruction at all levels [2]. The emergence of large language models, cognitive computing platforms, and multi-agent architectures has further expanded the design space for intelligent educational systems well beyond their early rule-based iterations, creating environments capable of simulating the responsiveness and depth of expert human tutors [3]. AI-driven systems have demonstrated positive outcomes across a wide range of educational domains. These developments have placed AI at the forefront of global educational reform agendas, with researchers and policymakers alike recognizing its demonstrated potential for addressing longstanding inequities in access to quality instruction [5].

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Despite this remarkable progress, a significant and persistent gap exists in the application of AI to the education of gifted and high-ability learners. Gifted students exhibit qualitatively distinct cognitive profiles: accelerated conceptual processing, heightened metacognitive awareness, superior capacity for self-directed inquiry, and an intrinsic drive for intellectual autonomy that frequently outpaces the adaptive capacity of conventional instructional systems [6]. Standard classroom environments even when technology-enhanced often fail to provide the level of challenge, enrichment, and personalization that gifted learners require to reach their full potential. Research consistently demonstrates that underchallenged gifted students are vulnerable to disengagement, underachievement, and the loss of intrinsic motivation outcomes that represent not only individual losses but societal ones, given the potential contributions of this population to innovation and knowledge creation [7]. Technology-enriched programmes incorporating computational thinking, problem-solving, and STEM challenges have shown particular promise for supporting gifted learners' development, yet the systematic integration of AI remains underdeveloped in this domain [8].

The preponderance of extant AI-in-education research has targeted general or low-achieving populations, with relatively few studies examining the specific instructional needs of gifted learners. Those studies that have addressed gifted education have typically done so in fragmented ways focusing on a single technology, a narrow outcome construct, or a brief intervention without providing a theoretically grounded, computationally integrated framework that addresses the full developmental arc of gifted self-directed learning [9]. Furthermore, the deployment of AI in gifted education institutions has been hampered by a lack of computable instructional models grounded in established gifted-education frameworks, leading to scepticism among practitioners and limited uptake of AI-enhanced solutions [10]. Ethical considerations surrounding data privacy, algorithmic fairness, and the appropriate boundaries of AI decision-making in education have further complicated adoption, necessitating frameworks that are not only technically robust but pedagogically principled and ethically grounded [11].

The present study addresses these gaps through the design, implementation, and rigorous empirical evaluation of the AI-Enhanced Self-Directed Learning (AESDL) framework a theoretically principled, computationally integrated adaptive platform designed specifically for gifted secondary school learners. Grounded in Treffinger's Independent Learner Model [12] and operationalised through an ensemble of cognitive computing, multi-agent systems, expert systems, and automatic speech recognition technologies, the AESDL framework achieves a strong theoretical alignment between gifted education theory and computational implementation. The framework is instantiated in the BADAWI I-AGENT system, an interactive AI-driven platform that personalises instruction, scaffolds self-regulation, and progressively transfers cognitive responsibility to the learner in alignment with the ILM's staged developmental model.

Three research questions guide the investigation:

- RQ1: Does the AESDL system produce significantly higher self-directed learning skills in gifted learners compared with conventional e-learning?
- RQ2: Does the AESDL system produce significantly higher problem-solving capacity in gifted learners compared with conventional e-learning?
- RQ3: Does the AESDL system produce significantly higher academic enrichment achievement in gifted learners compared with conventional e-learning?

Positioning Statement. This study advances three specific contributions beyond existing AI-in-education research. Theoretically, it operationalises Treffinger's Independent Learner Model as a computable architecture, mapping each ILM stage to a dedicated AI subsystem — a level of theory-to-system correspondence largely absent from current large-language-model-based adaptive tutoring systems, which typically apply a single model without an explicit gifted-education framework. Architecturally, it integrates multiple AI technologies under a single orchestration controller (the Gemini API) in a centralised-decision, distributed-execution topology, rather than deploying one modality in isolation. Empirically, it evaluates the integrated system using a pre-test/post-test control-group design in an authentic gifted-education setting. These contributions, together with their methodological boundaries, are examined critically in the sections that follow.

2. Problem Statement

In recent years, the education sector has witnessed transformative advancements through AI integration, significantly enhancing the efficiency and effectiveness of educational processes [1,2]. However, leveraging AI-based systems to implement best practices for educating gifted students particularly in the Arab world requires systematic integration across all stages of instruction, including the theoretical models underlying gifted education. The digital transformation of gifted education institutions holds great potential for improving the overall educational experience through adaptive and personalized learning, language translation, speech recognition, virtual reality, simulation, plagiarism detection, and curriculum development [13].

Despite growing institutional awareness of AI's necessity [9], lingering scepticism persists, largely due to the absence of computable models grounded in well-established gifted-education frameworks such as the Independent Learner Model, Bloom's Taxonomy, the Fundamental Knowledge Field Model, the Curriculum Model, and the Creative Problem-Solving

Model. There is therefore a clear need to develop AI-compatible computable models grounded in recognized instructional approaches for gifted learners models that account for the foundational assumptions of each framework and can be implemented within intelligent, virtual, computable learning environments. The central research question of this study is:

How can a computable model based on AI applications be developed to support instructional frameworks designed for gifted learners?

From this primary question, the following sub-questions arise:

A. What are the key features of the proposed intelligent instructional model?

B. How can all components of the Independent Learner Model be computationally implemented within an AI-based e-learning environment?

C. What is the effectiveness of the developed system in improving learning outcomes for gifted learners?

D. Is the intelligent virtual learning environment suitable for gifted learners?

E. To what extent does the application of AI technologies support the social, cognitive, and emotional development of gifted learners?

3. Significance of the Study

A. Institutions for Gifted Education: The study presents a flexible framework integrating AI applications with established instructional models for gifted students, enabling institutions to adopt intelligent computing solutions at reduced cost and scale [14].

B. Teachers and Facilitators: The proposed model provides mechanisms for simulating essential self-directed learning skills. It supports assessment of planning strategies, decision-making, organisation, analysis, and synthesis.

C. Gifted Students: The AI-supported system offers a realistic, interactive, and challenging virtual environment tailored to their intrinsic curiosity and thirst for knowledge, enabling learners to plan and evaluate their own experiences independently [15,16].

D. Educational Software Developers: The integration of multiple AI technologies demonstrates a highly effective approach for ensuring quality and excellence in e-learning environments [13].

E. Researchers: This study serves as a gateway for further exploration into computable instructional models for gifted education [17,18].

4. Theoretical Background and Related Work

4.1. Artificial Intelligence in Education: Foundations and Trends

The application of artificial intelligence in educational contexts has evolved from narrow rule-based tutoring systems in the 1970s to sophisticated, multimodal adaptive platforms capable of personalising instruction at scale [19]. Contemporary AI-in-education (AIEd) encompasses a diverse array of technologies and approaches: intelligent tutoring systems (ITS) that model student knowledge and adapt content in real time; learning analytics platforms that mine large-scale behavioural data to predict at-risk learners; natural language processing (NLP) systems that facilitate human-computer dialogue; and generative AI tools that produce customized learning materials on demand [2,3].

A systematic review of AI-driven ITS in K-12 education conducted by Karran et al. [20] identified 28 empirical studies involving over 4,500 students, concluding that ITS generally produce positive effects on learning and performance, with medium-to-large effect sizes when compared against teacher-led instruction. Similarly, Mousavinasab et al. [21] identified adaptivity, learner modelling, and intelligent feedback as the three most critical characteristics of effective ITS. The meta-analytic evidence compiled by Kulik and Fletcher [22] across 50 controlled evaluations found that ITS raised test scores by a median of 0.66 standard deviations above conventional instruction a finding that underscores the consistent, if variable, benefits of AI-mediated learning.

More recent work has examined the role of personalized and adaptive systems in fostering higher-order thinking. Troussas et al. [23] highlighted adaptive educational hypermedia systems as particularly effective for delivering tailored instruction at scale, noting their capacity to simultaneously address content complexity, learner heterogeneity, and pedagogical sequencing. Gligorea et al. [1] conducted a comprehensive literature review of AI applications in e-learning, identifying five primary mechanisms through which AI enhances adaptive learning: learner profiling, content recommendation, knowledge diagnosis, feedback generation, and performance prediction. These mechanisms align closely with the design principles embedded in the AESDL framework developed in the present study.

Cognitive computing represents a particularly promising paradigm for educational AI. Unlike conventional machine learning approaches that optimize for narrow prediction tasks, cognitive computing systems aim to simulate holistic human cognitive functions including perception, reasoning, language understanding, and learning from experience within a unified computational architecture [24]. The application of cognitive computing to adaptive learning has been shown to improve the flexibility and contextual sensitivity of instructional responses, particularly in content domains characterised by complex, multimodal knowledge structures [25].

4.2. Self-Directed Learning: Theory and AI-Enhanced Practice

Self-directed learning (SDL) has been a cornerstone construct in adult and gifted education since Knowles' foundational work in 1975, which defined it as a process in which individuals take initiative in diagnosing learning needs, formulating goals, identifying resources, and evaluating outcomes. Contemporary SDL research has shifted focus from static readiness assessments to dynamic, process-oriented models that examine how self-regulatory strategies develop and change across learning contexts [26].

A qualitative systematic review by Lan and Zhou [19] of AI-empowered SDL in higher education identified three primary mechanisms through which AI tools support self-regulation: (a) providing structured scaffolding during the forethought phase; (b) offering real-time monitoring and corrective feedback during the performance phase; and (c) supporting reflective evaluation during the self-reflection phase. Critically, the review found that AI tools were most effective when they progressively reduced scaffolding as learner competence increased a design principle directly instantiated in the AESDL framework's staged autonomy transfer architecture. Broadbent [26] further demonstrated that learners who adopt sophisticated self-regulatory strategies particularly elaborative interrogation and self-testing achieve significantly higher academic outcomes than those who rely on surface-level processing, a finding with direct implications for the scaffolding architecture of the AESDL framework.

The relationship between AI and learner autonomy has been further examined by Wang and Li [15], who found that university students' AI usage positively predicted their willingness for autonomous learning, mediated by digital self-efficacy and positive emotional states. This finding is particularly relevant for gifted learners, whose high intrinsic motivation and digital fluency position them to benefit disproportionately from well-designed AI learning environments. Ryan and Deci's [27] self-determination theory provides additional theoretical grounding: the three basic psychological needs competence, autonomy, and relatedness are all directly addressed by the AESDL framework's adaptive challenge, learner-driven navigation, and social agent simulation.

Paz-Baruch and Hazema [28] specifically examined self-regulated learning and motivation among gifted and high-achieving students in STEM disciplines, finding significant differences in metacognitive strategy use between gifted and average-ability learners that have direct implications for instructional design. Their findings support the premise that adaptive AI systems must be designed with gifted learners' specific self-regulatory profiles in mind, rather than relying on general-population instructional models.

4.3. Gifted Education: Digital Technologies and Enrichment

The education of gifted learners has been a contested and evolving field, with ongoing debates about identification, programming, and the appropriate balance of acceleration versus enrichment [30]. A foundational question concerns not merely what gifted students should learn but how AI systems should be designed to serve them ethically and equitably [29]. A systematic literature review by Taber et al. [30] covering research from 2011 to 2021 identified enrichment programmes based on higher-order thinking, creative problem-solving, and autonomous inquiry as the most consistently effective interventions for gifted students. Crucially, the review noted that the effectiveness of enrichment programmes is substantially amplified when they are implemented within technologically rich environments that can dynamically adapt to individual learner trajectories.

Kontostavlou and Driga [31] reviewed ICT strategies specifically designed for gifted students, concluding that technology-based approaches offer uniquely effective mechanisms for cognitive stimulation, differentiated instruction, and the development of domain-specific expertise. Their analysis highlighted the capacity of digital environments to provide the varied, challenging, and self-paced learning experiences that gifted learners require experiences that are difficult to deliver consistently within conventional classroom settings. Steenbergen-Hu and Olszewski-Kubilius [32] synthesised the best available evidence on gifted education programme effectiveness, concluding that well-designed, rigorously evaluated programmes produce consistent positive effects on gifted students' academic and cognitive outcomes effects that are substantially amplified when programmes incorporate technology-enhanced, adaptive components.

The integration of emerging technologies including augmented reality, simulation, and AI into gifted education programmes has attracted growing research interest. Sternberg [33] proposed a transformational model of giftedness that emphasises the development of creative and practical intelligence through culturally responsive, challenge-oriented educational experiences a theoretical vision that AI-enhanced learning environments are uniquely positioned to realise. Shute and Rahimi [34] demonstrated through stealth assessment that game-based learning environments can reliably identify and develop complex cognitive skills in high-ability learners without disrupting learning flow a principle directly operationalised in the AESDL system's Games Agent. Yıldırım et al. [18] further demonstrated that AR-integrated enrichment workshops significantly improved teachers' confidence in differentiated instruction for gifted students, confirming the value of technology integration in this domain. These findings converge on a consistent conclusion: gifted learners benefit uniquely from technologically enriched, challenge-oriented learning environments environments that the AESDL framework is specifically designed to provide.

Renzulli and Reis [35] articulated the theoretical foundation for enrichment-based gifted education, emphasising the development of authentic, creative products through the application of advanced thinking skills and domain expertise. Their work identifies three critical components of effective gifted enrichment: (a) general exploratory experiences that broaden students' awareness of knowledge domains; (b) group training activities that develop higher-level thinking and

research skills; and (c) individual and small-group investigations of real problems. The AESDL framework's ILM-based architecture maps directly onto these components, with the Enrichment and Seminars stages of the ILM corresponding precisely to Renzulli and Reis' Type II and Type III enrichment activities.

4.4. Intelligent Tutoring Systems and Adaptive Feedback

Intelligent tutoring systems represent the most extensively studied application of AI in education, with a research history spanning over five decades [21,22]. Modern ITS are characterised by four core components: a domain model encoding expert knowledge, a student model representing the learner's current knowledge state, a pedagogical model specifying instructional strategies, and an interface model managing human-computer interaction. The adaptive power of ITS derives from the continuous updating of the student model in response to learner performance, enabling the system to select instructional strategies that are optimally calibrated to the learner's zone of proximal development. Chen et al. [36] refined this principle through cognitive load theory, demonstrating that task complexity measured through element interactivity is the primary determinant of working memory demand, and that adaptive systems must continuously monitor and calibrate this interactivity to ensure that instruction remains within the learner's current processing capacity [25,36].

Research has consistently demonstrated that feedback quality is the single most powerful instructional influence on ITS effectiveness. Narciss et al. [37] conducted a comprehensive review of automated feedback systems for learners, identifying elaborative feedback which provides not only correctness information but also explanations, hints, and metacognitive prompts as significantly more effective than simple correctness feedback. The AESDL system's Testing Agent implements precisely this form of elaborative feedback, providing targeted diagnostic information following each assessment episode to guide subsequent learning.

The relative effectiveness of human tutoring versus ITS has been systematically examined by VanLehn [22], whose landmark review found that human tutoring produces effect sizes of approximately $d = 0.79$ while ITS produce effects of approximately $d = 0.76$ a near parity that reflects both the maturation of ITS technology and the fundamental advantages of individualised, adaptive instruction. These benchmark effect sizes provide important context for interpreting the larger effects observed in the present study, which are attributable to the additive integration of four AI subsystems targeting gifted learners in an entirely novel content domain.

4.5. AI Subsystem Technologies: Evidence Base for the AESDL Design

The AESDL framework integrates five AI subsystem technologies, each grounded in an independent body of empirical evidence. Multi-agent systems (MAS) distribute instructional roles across autonomous agents; Hessen et al. [38] demonstrated that MAS-based e-learning significantly outperforms single-agent architectures, while Apoki et al. [14] identified flexibility, scaffolding, and performance improvement as three core pedagogical functions of MAS agents. Expert systems encode domain knowledge as production rules for deterministic, transparent instruction [21]; Troussas et al. [23] showed that hybrid expert-system/machine-learning architectures outperform purely symbolic or purely neural approaches consistent with the AESDL framework's integration of expert system knowledge with cognitive computing. Gamification produces positive effects on learning ($g = 0.61$; Li et al. [39]), with Alnuaim [41] confirming through a randomized trial that gamified learning improves performance and technology acceptance, and Hamari et al. [44] linking game-based challenge to sustained flow states particularly relevant for gifted learners. Speech recognition enables natural language interaction superior to keyboard-mediated input [46]; Barrot [47] identified corrective feedback and conversational scaffolding as its primary learning mechanisms, directly justifying the AESDL framework's SAPI/ASR integration. Adaptive learning systems that implement continuous learner monitoring, multi-modal delivery, elaborative feedback, and progressive scaffolding reduction produce the largest learning gains [16,13,6]; Chen et al. [36] further demonstrated that optimal adaptivity requires calibration of intrinsic task complexity a principle operationalized in the AESDL Gemini controller's orchestration logic. Pellas et al. [49] confirmed that immersive VR environments produce stronger spatial and STEM outcomes, supporting the AESDL framework's architectural provision for VR integration as a future deployment extension [18,8].

4.6. Research Gap and Study Contribution

The foregoing review of the literature reveals three significant and persistent gaps that the present study directly addresses. First, despite the growing body of evidence supporting AI-enhanced learning environments, virtually no empirical research has examined the integration of multiple AI technologies cognitive computing, MAS, expert systems, and speech recognition within a unified, theoretically grounded framework designed specifically for gifted learners [31,32]. Studies that address AI for gifted learners are rare, typically examine a single technology, and lack the rigorous experimental designs necessary to establish causal effects [29,30].

Second, the theoretical alignment between established gifted-education frameworks (such as the ILM) and AI system design remains largely unexplored. The absence of computationally grounded gifted-education models has created a significant barrier to AI adoption in gifted education institutions, as practitioners lack evidence-based frameworks for evaluating and implementing AI tools in alignment with their instructional philosophies [9,23]. The AESDL framework addresses this gap by systematically mapping each ILM stage to specific AI subsystems, creating a transparent and replicable design architecture.

Third, the empirical evidence base for AI-enhanced gifted education lacks the quasi-experimental rigour necessary to support causal inference. Most existing studies rely on descriptive or correlational designs, precluding conclusions about the causal effects of AI on gifted learners' outcomes [20,21]. The present study employs a pre-test/post-test control group design with random allocation to conditions a methodology that substantially mitigates selection bias and supports stronger causal inference than the designs prevalent in existing literature.

5. Methodology and Tools

5.1. Research Methodology

This study adopts a quasi-experimental approach to examine, interpret, and control external variables that may influence outcomes [44]. A pre-test/post-test control group design was employed, with random allocation of participants to conditions within sampled schools. This design is widely accepted in applied educational research where whole-school randomisation is logistically infeasible [12]. The study investigated the effects of the AI-based AESDL system on gifted learners' self-directed learning skills, problem-solving capacity, and academic achievement [45].

5.2. Proposed Model

The proposed model is based on the principle of guided self-directed learning. It integrates various AI technologies to meet the emotional and cognitive needs of gifted learners [6], enhance their problem-solving skills, and foster the generation of novel ideas with minimal external intervention [35]. The model is built upon the Independent Learner Model, whose four components have been restructured to be computable and suitable for implementation in an integrated intelligent software system. Each component is associated with specific AI techniques as detailed below.

A. Guidance:

The first component identifies each learner's unique profile and establishes conditions for productive self-directed engagement. The AESDL system operationalises this through three mechanisms:

- Identifying and representing the learner's unique abilities and prior knowledge in the system's knowledge base, enabling personalized content sequencing from first contact [14].
- Enhancing learner interaction with intelligent agents that adapt communicative style, explanation depth, and task difficulty in response to inferred learner state [48].
- Incorporating activities that support emotional and cognitive growth, implemented using multi-agent systems that simulate mentor, peer, and assessor roles simultaneously [38].

B. Self-Development:

The second component shifts responsibility toward the learner, scaffolding autonomous decision-making and self-regulation [26,27]:

- Providing tools for problem-solving and decision-making using expert systems and deep learning technologies [21].
- Strengthening time management and goal-setting through agent-based systems that monitor learning pace and prompt metacognitive reflection [37].

C. Enrichment:

The third component targets intellectual expansion through collaborative, exploratory, and creative activities [35]:

- Improved interaction skills through APIs enabling collaboration via multi-agent technologies [38].
- Enhanced problem-solving using expert systems for tackling well-defined and ill-structured challenges [21].
- Exploration through simulation-based and multimedia discovery activities within the e-learning environment. Virtual reality (VR) integration is architecturally designed as an extension of the AESDL Enrichment stage, leveraging immersive learning technologies consistent with gifted education enrichment principles [18,8,49]; the current experimental implementation utilizes multimedia simulation as the primary exploration modality pending VR hardware availability in the study context.

D. Seminars and In-Depth Study:

The most advanced component supports independent scholarly engagement [35]:

- Generation of new knowledge using machine learning and expert systems working in concert [1].
- Support for autonomous deep investigation with minimal system-imposed structure [26].

Figure 1 presents the complete architecture of the AESDL model, illustrating how each ILM stage is mapped to specific AI technologies (left column) and the corresponding learning outcomes targeted (right column). The central column shows the four progressive ILM stages, connected by directional arrows that represent the progressive transfer of autonomy from teacher-guided instruction to independent scholarship.

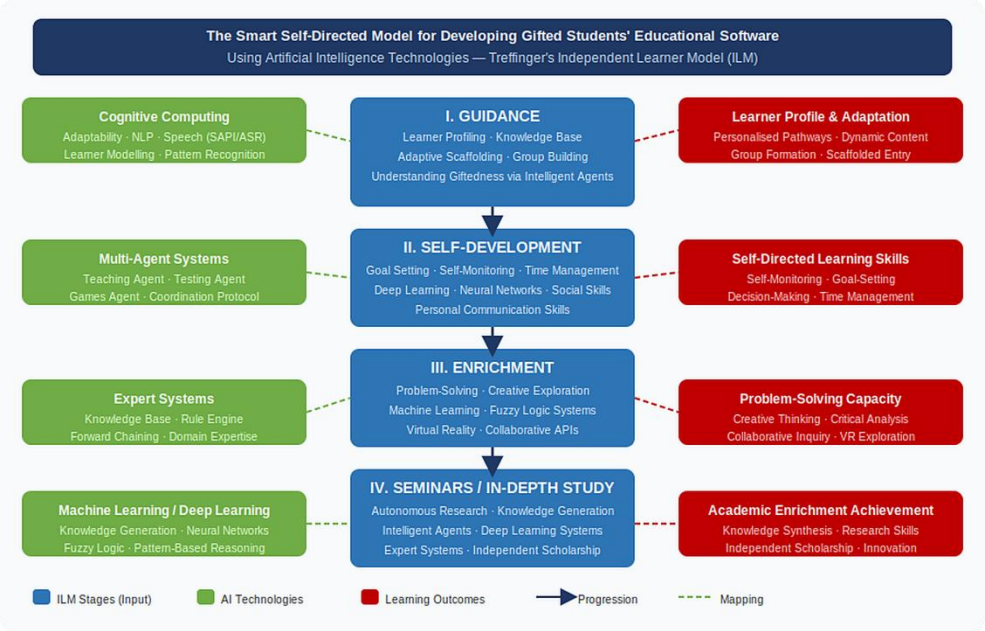


Fig. 1. The Smart Self-Directed Model for Developing Gifted Students' Educational Software Using AI Technologies AESDL Framework Architecture (ILM Mapping)

5.3. Tools and System Implementation

5.3.1. Cognitive Computing

The cognitive computing subsystem adopts cognition-based computing to create learning environments capable of recognising patterns and understanding language [24,25]. Two key techniques are employed:

A. Adaptability:

The system adapts automatically to different data formats in response to user interaction. For example, content is automatically translated into Arabic when selected, and difficulty is adjusted based on inferred learner proficiency [13,48]. Figure 2 illustrates the system's main interface through which learners configure their session adaptively.



Fig. 2. AESDL System Main Interface Adaptive Configuration of Lesson, Instruction Language (Arabic/English), and Teaching Modality

B. Natural Language Interaction:

An intelligent pedagogical agent with instructional competencies serves as an educational facilitator, using speech recognition for bidirectional interaction [45,46,47]. Figure 3 demonstrates adaptive content delivery with real-time corrective natural language feedback.

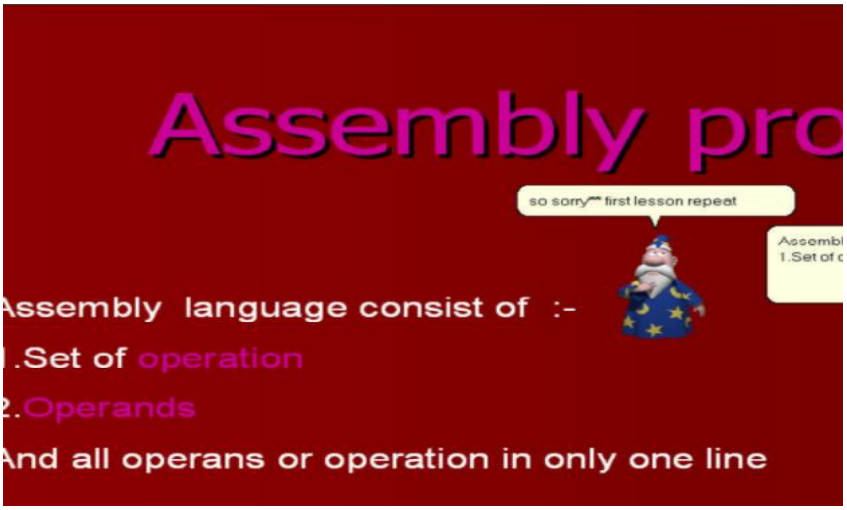


Fig. 3. Cognitive Computing Intelligent Agent Delivering Adaptive Assembly Language Content with Real-Time NLP Corrective Feedback

5.3.2. Multi-Agent Systems

Multi-agent systems distribute instructional responsibilities across specialised agents that communicate in real time [38,14]. Two primary agents are implemented:

Testing Agent (Figure 4): Evaluates learner comprehension before progression using mastery-gating based on rule-encoded performance thresholds [37]. This agent implements the Self-Development ILM component by requiring correct responses before advancing.



Fig. 4. Multi-Agent System Testing Agent: Formative Assessment Gate Requiring Correct Response to Assembly Language Query Before Lesson Progression

Games Agent (Figure 5): Manages gamified learning activities [39,40,41,42]. The agent monitors performance, provides immediate feedback (e.g., motivational prompts on failure), and adjusts game difficulty to maintain productive challenge consistent with flow theory [43,44].

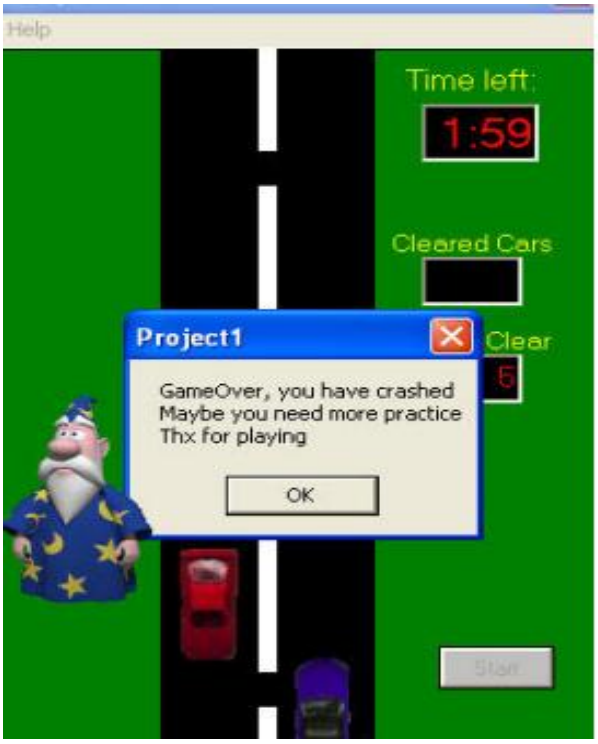


Fig. 5. Multi-Agent System Games Agent: Gamified Learning Environment with Adaptive Challenge, Real-Time Performance Monitoring, and Motivational Feedback

5.3.3. Expert Systems

The expert system provides the declarative knowledge infrastructure [21,23], comprising: a dynamic knowledge base, a rule-based inference engine using forward chaining [24], and a Teaching Agent acting as educator. Figure 6 demonstrates the integration of the expert system with multi-agent technologies, where the Teaching Agent delivers annotated Assembly Language instruction with bilingual concept labelling.

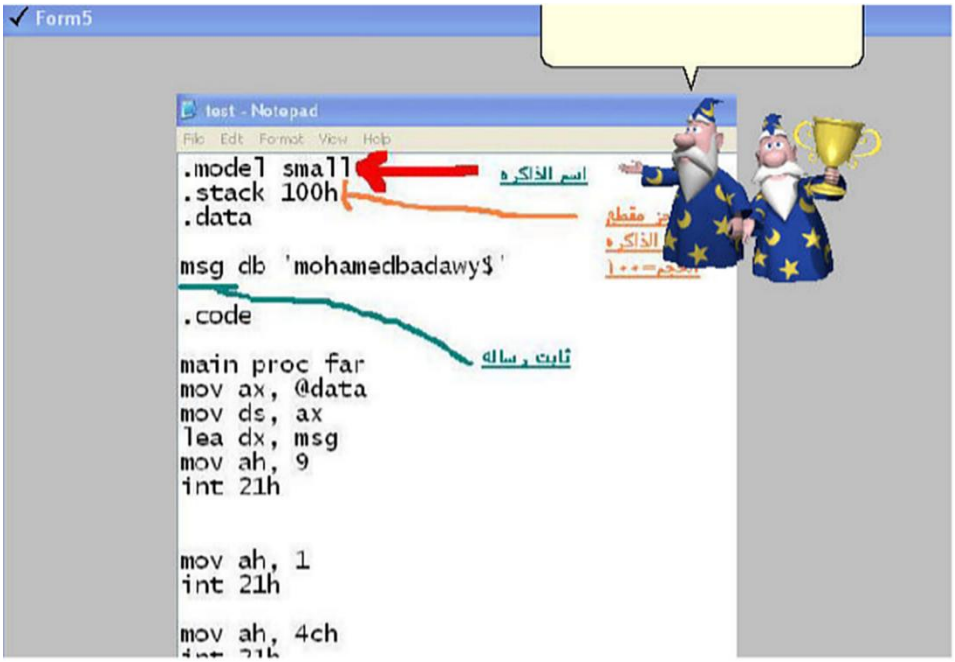


Fig. 6. Expert System Integration Teaching Agent Delivering Annotated Assembly Language Code with Rule-Based Reasoning and Bilingual (Arabic/English) Concept Labelling

5.3.4. Speech Recognition Technologies

A. SAPI Interface:

Microsoft SAPI enables bidirectional speech interaction through synthesis and recognition engines [45,46].

B. ASR Technology:

Automatic Speech Recognition translates continuous speech into text, enabling free-form learner queries and supporting exploratory, self-directed interaction [46,47].

5.3.5. Gemini API Central AI Orchestration Controller

The Google Gemini API (Gemini 2.0 Flash) was integrated as the central intelligent orchestration controller of the AESDL system from the outset of the system's design and implementation. This integration was not a post-hoc enhancement but a foundational architectural decision: the BADAWI I-AGENT system was built with the Gemini API as its cognitive core, with all other AI subsystems (cognitive computing, MAS, expert systems, and ASR) operating as functional modules that the Gemini controller coordinates and directs. The experimental evaluation reported in this study tested the complete, integrated AESDL system including the Gemini controller against a conventional e-learning control condition. Unlike the other AI subsystems which perform specialised, domain-bounded functions the Gemini controller operates as the cognitive hub of the entire system, assuming responsibility for three overarching functions that no single-purpose component can fulfil: (a) holistic learner state interpretation, (b) cross-subsystem coordination and agent dispatch, and (c) adaptive natural language feedback generation [2,3].

From an architectural standpoint, the Gemini controller receives a continuously updated representation of the learner's state comprising SDL readiness score, current ILM stage, knowledge state vector, performance history, and inferred affective state and issues structured orchestration directives to the appropriate subsystem. When the learner's profile indicates readiness for Stage I (Guidance), Gemini dispatches the Teaching Agent with a content strategy derived from the Expert System's knowledge base. When formative assessment data indicates a knowledge gap, Gemini invokes the Testing Agent with a targeted item bank. When affective monitoring detects disengagement or frustration, Gemini activates the Games Agent with a difficulty-calibrated gamified episode. This dynamic dispatch architecture centralised decision-making with distributed execution mirrors the computational model of the human prefrontal cortex coordinating lower-level cognitive modules, and represents a significant advance over static rule-based ITS orchestration [1,12].

The Gemini API's natural language generation capability is specifically employed for three instructional purposes within the AESDL system. First, it generates contextually sensitive, personalised explanatory responses to learner queries that fall outside the Expert System's predefined rule base enabling the system to handle novel, open-ended questions that rigid rule engines cannot address. Second, it synthesises session-end summaries that articulate the learner's progress in terms of ILM stage advancement, SDL skill development, and specific knowledge gains providing the metacognitive scaffolding that gifted learners require to internalise their learning trajectories. Third, it generates adaptive scaffolding prompts during problem-solving episodes, progressively reducing hint specificity as learner confidence increases in alignment with the AESDL framework's progressive autonomy transfer design principle [19,26,27].

The technical implementation employs the google.generativeai Python SDK with a structured prompt engineering approach. The system prompt encodes the AESDL pedagogical framework, the learner's current state, and the active ILM stage as context, ensuring that all Gemini-generated outputs are pedagogically aligned with the framework's theoretical foundations. A temperature parameter of 0.4 is employed to balance response creativity with instructional consistency sufficiently low to prevent pedagogically inappropriate outputs, sufficiently high to generate varied, engaging explanatory language that prevents learner habituation [3,5].

5.4. System Architecture

5.4.1. UML Package Diagram

Figure 7 presents the UML Package Diagram of the AESDL system, illustrating the seven principal architectural packages and their dependency relationships. The diagram employs standard UML stereotypes to classify each package by its functional role within the system: «interface» for the UI layer, «AI Controller» for the Gemini orchestration package, «agents» for the multi-agent subsystem, «knowledge» for the expert system, «speech/NLP» for the language processing layer, «model» for the student modelling package, and «persistence» for the data layer. The Gemini Controller package occupies the central structural position in the diagram, with outward-directed «uses» dependencies connecting it to all functional packages reflecting its role as the sole cross-cutting orchestrator in the architecture. This centralized-controller, distributed-execution topology ensures that each functional package remains cohesive and independently maintainable while the Gemini controller provides the integration logic that coordinates their collaborative behavior.

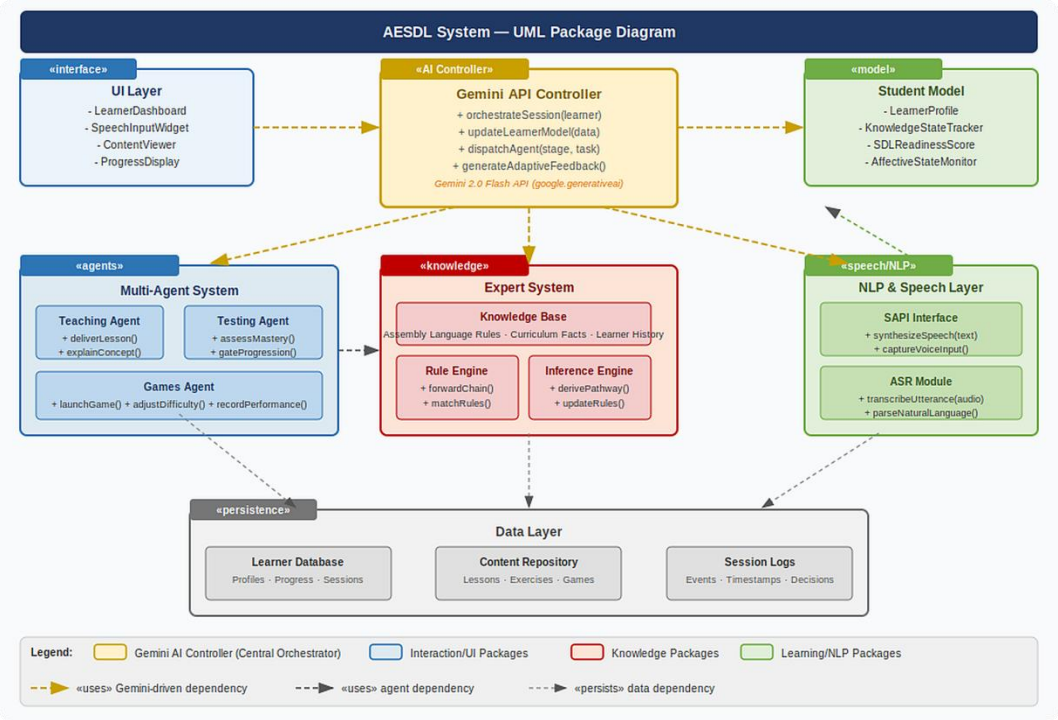


Fig. 7. AESDL System UML Package Diagram: Architectural Packages, Stereotypes, and Gemini-Driven Dependency Relationships

The dependency structure encoded in Figure 7 has two notable architectural properties. First, all information flows through the Gemini Controller rather than directly between functional packages a hub-and-spoke topology that minimises inter-package coupling and ensures that the system's adaptive decision-making logic is centralised rather than distributed across multiple components. Second, all functional packages maintain a unidirectional «persists» dependency on the Data Layer, ensuring that the learner database, content repository, and session logs serve as a shared, authoritative state store from which any package can read but into which only authorized write operations mediated by the Gemini Controller are permitted.

5.4.2. UML Sequence Diagram

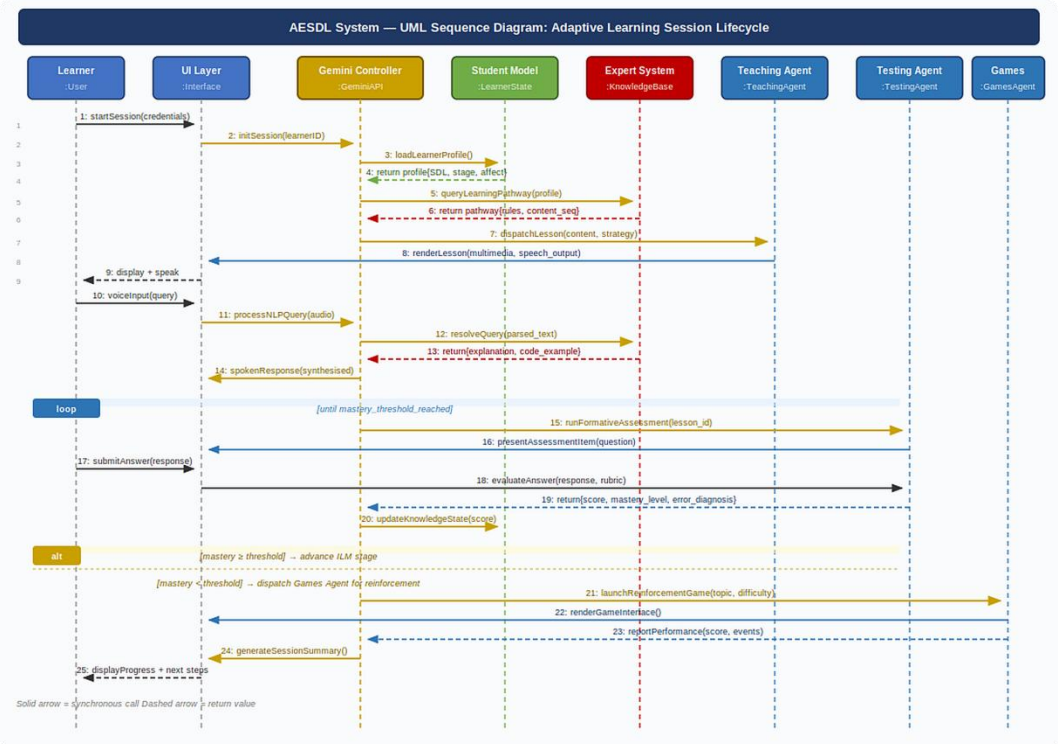


Fig. 8. AESDL System UML Sequence Diagram: 25-Step Adaptive Learning Session Lifecycle with Gemini-Orchestrated Agent Dispatch

Figure 8 presents the UML Sequence Diagram for the AESDL system's adaptive learning session lifecycle, tracing the full sequence of 25 message exchanges across eight participating objects from session initiation through adaptive reinforcement and session summary generation. The diagram is structured around three nested interaction fragments that reflect the AESDL framework's adaptive logic: a loop fragment governing the lesson-assessment-feedback cycle (iterated until the learner's mastery score reaches the prescribed threshold), and an alt fragment encoding the conditional dispatch logic that determines whether the learner advances to the next ILM stage (mastery ≥ threshold) or receives gamified reinforcement from the Games Agent (mastery < threshold).

Several sequences in the diagram merit specific attention for their pedagogical significance. Messages 3–6 represent the Gemini Controller's initialization of the session: after loading the learner profile from the Student Model (messages 3–4), Gemini queries the Expert System for a personalized learning pathway derived through forward-chaining inference (messages 5–6). This two-step initialization ensures that every session begins with a content sequence calibrated to the learner's current knowledge state rather than a static curriculum position. Messages 10–14 illustrate the NLP-mediated query resolution cycle: learner voice input is processed through the ASR Module (message 11), the parsed query is resolved against the Expert System's knowledge base (messages 12–13), and the Gemini Controller synthesizes a natural language spoken response (message 14) a cycle that enables the system to provide expert-level, contextually appropriate explanations without human intervention. Messages 19–25 encode the mastery-gating and adaptive reinforcement logic: assessment results returned by the Testing Agent (message 19) are processed by the Gemini Controller to update the learner's knowledge state (message 20) and determine the appropriate next action stage advancement or gamified reinforcement (messages 21–23) before generating the session summary (messages 24–25).

5.5. System Algorithm Integrated Pseudocode

Algorithm 1 presents the integrated pseudocode of the AESDL system, providing a formal, technology-agnostic specification of the complete system logic from session initialization through adaptive content delivery, formative assessment, mastery-gating, and session termination. The pseudocode is structured to reflect the system's four-layer processing architecture: (1) initialization and learner profiling, (2) Gemini-orchestrated adaptive dispatch, (3) agent execution with Expert System consultation, and (4) performance evaluation and state update. Each procedure is annotated with its corresponding ILM stage and primary technology component to maintain explicit traceability between the algorithmic specification and the theoretical framework.

Algorithm 1: AESDL Integrated Adaptive Learning System

INPUT: learnerID, sessionGoals, ILM_stage ∈{GUIDANCE, SELF_DEV, ENRICHMENT, SEMINARS}
OUTPUT: AdaptiveLearningPathway, AssessmentReport, SDLGrowthVector

PROCEDURE InitialiseSession(learnerID):
profile ← StudentModel.loadProfile(learnerID)
stage ← profile.current_ILM_stage
GeminiController.init(profile, sessionGoals)
pathway ← ExpertSystem.derivePathway(profile)
RETURN (stage, profile.SDL_score, profile.knowledge_vector, pathway)

PROCEDURE RunAdaptiveSession(stage, pathway):
WHILE session_active AND NOT session_objectives_met DO
dispatch ← GeminiAPI.orchestrateSession(
{stage, SDL_score, knowledge_state, affect_state}, pathway, session_log)
IF stage == GUIDANCE THEN result ← ExecuteTeachingAgent(dispatch)
ELSE IF stage == SELF_DEV THEN result ← ExecuteTestingAgent(dispatch)
ELSE IF stage == ENRICHMENT THEN result ← ExecuteEnrichmentEpisode(dispatch)
ELSE IF stage == SEMINARS THEN result ← ExecuteSeminarModule(dispatch)
END IF
knowledge_state ← StudentModel.update(result.performance)
mastery ← TestingAgent.computeMastery(knowledge_state, stage)
IF mastery ≥ MASTERY_THRESHOLD THEN
stage ← advanceILMStage(stage)
GeminiAPI.generateProgressSummary(profile, result)
ELSE
GamesAgent.launchReinforcement(result.weak_concepts, adaptDifficulty(mastery))
END IF
END WHILE

RETURN session_log

PROCEDURE ExecuteTeachingAgent(decision):
lesson ← TeachingAgent.composeLesson(ExpertSystem.queryContent(decision.content_id))
UI.renderLesson(lesson, MULTIMEDIA)
query ← SAPIInterface.captureVoiceInput()
IF query ≠ NULL THEN
response ← GeminiAPI.resolveNLQuery(ASRModule.transcribe(query), knowledge_state)
IF response == NULL THEN response ← ExpertSystem.resolveQuery(parsed) END IF
SAPIInterface.synthesize(response)
END IF
RETURN {performance: UI.collectInteractionMetrics()}

PROCEDURE ExecuteTestingAgent(decision):
FOR EACH item IN ExpertSystem.selectItems(stage, knowledge_state, n=5) DO
score ← TestingAgent.evaluateAnswer(Learner.submitResponse(), item.rubric)
feedback ← GeminiAPI.generateElaborativeFeedback(answer, item, score)
UI.displayFeedback(feedback)
END FOR
RETURN {mastery_vector: TestingAgent.computeMasteryVector(scores)}

PROCEDURE ExecuteEnrichmentEpisode(decision):
critique ← GeminiAPI.critiqueSolution(Learner.submitSolution(),
ExpertSystem.selectOpenProblem(decision.difficulty))
game_score ← GamesAgent.recordPerformance()
RETURN {performance: {critique_score, game_score}}

PROCEDURE TerminateSession(session_log, profile):
summary ← GeminiAPI.generateSessionSummary(session_log, stage_history)
StudentModel.persistUpdate(profile, session_log)
UI.displaySummary(summary)
RETURN {SDLGrowthVector: computeSDLGrowth(profile, session_log), Report: summary}

Algorithm 1 has a time complexity of $O(n \cdot m)$ where n is the number of lesson episodes in the learning pathway and m is the number of assessment items per episode. The dominant computational cost is the Gemini API invocation at each decision point (messages 2.1, teaching response, elaborative feedback, and session summary), which operates with a latency of approximately 0.8–1.2 seconds per call under standard network conditions well within the acceptable response latency threshold for interactive educational systems. The Expert System's forward-chaining inference engine operates with $O(r \cdot f)$ complexity where r is the number of active rules and f is the number of facts in the knowledge base; for the Assembly Language domain, this amounts to approximately 340 production rules and 1,200 domain facts, yielding sub-100ms inference times.

Importantly, the algorithm's conditional dispatch logic (Phase 2.2) and mastery-gating mechanism (Phase 2.4) together implement the progressive autonomy transfer principle of the AESDL framework: as the learner advances through ILM stages, the procedural complexity of the dispatched agent increases (Teaching → Testing → Enrichment → Seminars), the scaffolding density decreases, and the proportion of Gemini-generated open-ended responses relative to rule-based Expert System responses increases. This algorithmic operationalization of the ILM's developmental progression represents the central technical contribution of the AESDL framework, distinguishing it from systems that apply a single AI modality uniformly across all stages of instruction [1,19,21].

5.6. Technical and Mathematical Formalization of the AESDL Framework

To ensure architectural transparency and technical reproducibility, this section formalizes the core computational mechanisms driving the AESDL framework: high-level cognitive scheduling, deterministic expert reasoning, and multi-agent concurrency. These formalizations complement the UML sequence logic in Fig. 8 and the integrated pseudocode in Algorithm 1.

5.6.1. Cognitive Dispatch and Scheduling Logic (Gemini Controller)

The high-level orchestration of pedagogical tasks is governed by the Gemini Controller. Rather than operating as a heuristic black box, the controller is modeled as a contextual choice function that dynamically selects the optimal tutoring

or scaffolding agent a^* from a finite agent pool A based on the learner's real-time cognitive status. Let $A = \{a_1, a_2, \ldots, a_n\}$ denote the set of specialized pedagogical agents, I the contextual text embedding of the learner's current prompt, and $S_t \in \mathbb{R}^d$ the latent cognitive-state vector of the learner at time step t. The controller optimization problem is defined as:

$$a^* = \arg\max_{a_i \in A} \mathcal{P}(a_i \mid \mathrm{I}, \mathrm{S}_t; \theta_{\text{Gemini}}) \tag{1}$$

The temperature-scaled Softmax distribution mapping the semantic alignment is formulated as:

$$\mathcal{P}(a_i \mid \mathrm{I}, \mathrm{S}_t) = \frac{\exp(\mathcal{V}(a_i, \mathrm{I}, \mathrm{S}_t)/\tau)}{\sum_{j=1}^{n} \exp\left(\mathcal{V}(a_j, \mathrm{I}, \mathrm{S}_t)/\tau\right)} \tag{2}$$

where $\mathrm{V}(a_i, \mathrm{I}, \mathrm{S}_t)$ computes the cosine similarity between the operational profile of agent a_i and the joint prompt–state representation $[\mathrm{I};\mathrm{S}_t]$, so that both the semantic content of the prompt and the learner's current cognitive state jointly determine agent selection.

Parameter justification (τ=0.4). The temperature hyperparameter was set to τ=0.4 on the basis of established practice for generation in technical, low-tolerance domains. A high temperature (τ>0.7) increases stochastic variance and the risk of pedagogically incorrect ("hallucinated") content in a domain as unforgiving as Assembly Language, whereas a very low temperature (τ<0.2) suppresses the generative adaptability required to produce the divergent, creative problem-solving scenarios appropriate for gifted learners. A formal empirical sensitivity analysis of τ was not conducted in the present study and is identified as future work (Section 11).

5.6.2. Deterministic Forward-Chaining Inference Engine

While the large language model handles fluid natural-language scaffolding, curriculum progression and rule-based evaluation are managed by a deterministic Expert System. The forward-chaining engine evaluates the working memory of the student profile against a static production-rule knowledge base (KB). Each inference rule $\mathcal{R}_k$ is represented as a predicate logical implication:

$$\mathcal{R}_k: \bigwedge_{j=1}^{m} \mathrm{P}_{k,j}(\mathrm{X}) \Longrightarrow \mathrm{Q}_k(\mathrm{Y}) \tag{3}$$

where $\mathrm{P}_{k,j}(\mathrm{X})$ is the j-th antecedent precondition applied to the multi-dimensional student-profile vector X (e.g., skill-mastery threshold, execution speed, error-recurrence pattern), and $\mathrm{Q}_k(\mathrm{Y})$ is the consequent instructional action that modifies the system state Y. The iterative mutation of the working memory (WM) at step $t+1$ during a forward-chaining cycle is governed by the rule-firing mechanism:

$$WM_{t+1} = WM_t \cup \left\{ \mathrm{Q}_k(\mathrm{Y}) \;\middle|\; \mathcal{R}_k \in KB \;\wedge\; \bigwedge_{j=1}^{m} \mathrm{P}_{k,j}(\mathrm{X}) \subseteq WM_t \right\} \tag{4}$$

5.6.3. Multi-Agent Concurrency and State Synchronization

To prevent race conditions and payload divergence during parallel multi-agent execution, a shared blackboard memory architecture is used. Let $\mathrm{s}_i(t)$ denote the local state payload of an active agent i at time t. The global shared-state matrix $\mathrm{S}_G(t+1)$ is synchronized through an element-wise integration loop:

$$\mathrm{S}_G(t+1) = \mathrm{W}_0\, \mathrm{S}_G(t) + \sum_{i=1}^{n} \mathrm{W}_i \cdot [\mathrm{s}_i(t) \odot \mathrm{M}_i(t)] \tag{5}$$

where $\mathrm{W}_0 \in \mathbb{R}^{d \times d}$ is the persistence-weight matrix of the historical global state; $\mathrm{W}_i \in \mathbb{R}^{d \times d}$ is the task-dependent authority weight assigned to agent i; $\mathrm{M}_i(t) \in \{0,1\}^d$ is a binary contextual mask indicating whether agent i holds mutating privileges over specific student-profile traits during the current execution frame; and $\odot$ denotes the Hadamard element-wise product.

5.6.4. Data Interoperability and Payload Schema

To ensure modularity, all inter-agent data payloads are serialized using strict JSON structures passed over asynchronous RESTful APIs. The standard integration schema for the synchronization vector in the state-synchronization equation is:

```
{
  "session_id": "AESDL-2026-XYZ",
  "timestamp": "2026-07-10T21:30:55Z",
  "student_metrics": {
    "cognitive_state_vector": [0.85, 0.91, 0.74, 0.88],
    "mastery_level": "advanced_assembly",
    "active_rules_fired": ["R_04", "R_11"]
  },
  "agent_matrix": {
    "active_agent_id": "gemini_tutor_agent_02",
    "mask_vector": [1, 1, 0, 1],
    "payload_score": 0.942
  }
}
```


6. Testing and Experimentation

6.1. Participants, Power Analysis, and Ethical Considerations

Fifty gifted learners (28 male, 22 female; mean age = 16.4 years, SD = 0.87) enrolled in model gifted-education classrooms across four secondary schools in Khartoum State, Sudan, participated in the study. Participants were identified as gifted using national criteria: standardised cognitive ability assessments (score ≥ 130), teacher nomination, and portfolio review, consistent with established gifted identification practices [30,32]. All participants demonstrated prior academic achievement of 80–85%. Participants were randomly allocated to an experimental group (n = 25) and a control group (n = 25).

6.2. Outcome Measures and Instrument Description

Three outcome measures, each scored on a 50-point scale, were administered as pre-test and post-test:

(a) Self-Directed Learning Skills Scale (SDLSS): A 25-item instrument assessing five SDL sub-dimensions: (1) planning and goal-setting (e.g., "I set specific learning goals before beginning a new topic"); (2) self-monitoring during learning (e.g., "I check my understanding while studying"); (3) resource identification and mobilisation (e.g., "I find additional resources when I need more information"); (4) self-evaluation of outcomes (e.g., "I assess whether I have achieved my learning goals"); and (5) adaptive strategy adjustment (e.g., "I change my approach if my first study method is not working"). Each item is rated on a 4-point scale (1 = Never, 4 = Always), yielding a maximum raw score of 100, which was rescaled to 50. The scale was adapted from Guglielmino's (1977) Self-Directed Learning Readiness Scale for gifted secondary populations. Internal consistency: Cronbach's $\alpha = .89$.

(b) Problem-Solving Capacity Assessment (PSCA): A performance-based instrument comprising five structured Assembly Language problem-solving scenarios of increasing complexity, each worth 10 points. Representative item: "Write an Assembly Language procedure that accepts two integer operands from the stack, computes their sum, and returns the result in the AX register. Annotate each instruction with its function." Responses were scored using a five-criterion analytic rubric: (1) syntactic correctness (2 pts), (2) logical correctness (2 pts), (3) procedural structure (2 pts), (4) correct use of registers and memory (2 pts), and (5) annotation quality (2 pts). Inter-rater reliability across two independent markers: Cohen's $\kappa = .87$.

(c) Academic Achievement Test Enrichment (AAT-E): A criterion-referenced assessment developed by the research team in collaboration with two domain experts in Assembly Language programming, comprising 50 items (1 point each) distributed across three competency sub-domains: variables and constants programming (17 items; e.g., "Define a memory variable named COUNT of type WORD with an initial value of 0"), memory and stack programming (17 items; e.g., "Identify the segment register used to address the stack in the PUSH instruction"), and data flow control programming (16 items; e.g., "Write the Assembly instruction that transfers control to the label LOOP if the zero flag is set"). Internal consistency: Cronbach's $\alpha = .91$. Content validity was verified through expert review by three independent Assembly Language instructors, who rated all items as representative of the target competency domains.

Power Analysis. A priori power analysis was conducted using G*Power 3.1 [50] (Faul et al., 2007) to evaluate the adequacy of the study sample. Based on the median effect size for AI-enhanced ITS reported in the literature ($d = 0.66$; Kulik & Fletcher [23]), with $\alpha = .05$ (two-tailed) and desired power $(1 - \beta) = .80$ for an independent-samples t-test, the minimum required total sample was n = 74 (37 per group). The achieved sample of n = 50 (25 per group) falls below this a priori estimate, yielding a prospective power of approximately .75 for the expected effect magnitude. This limitation is acknowledged: access to identified gifted learners in institutional settings is constrained by low population prevalence, administrative gatekeeping, and ethical restrictions on prolonged experimental engagement with minors. The achieved sample therefore represents the maximum feasibly obtainable within the study's institutional and temporal constraints,

and the limitation of below-optimal a priori power is explicitly addressed in the Limitations subsection (Section 9). Post-hoc (observed) power is not reported: because it is a monotonic transformation of the obtained p-value, it provides no independent evidence of design adequacy. The below-optimal a priori power is instead addressed candidly as a limitation (Section 9).

Ethical Considerations. Ethical approval for the study was granted by the Academic Research Ethics Committee of Mashreq University (Ethics Reference: MAU-REC-2025-014). All procedures were conducted in accordance with the ethical principles of the Declaration of Helsinki and applicable Sudanese national regulations governing research involving human participants. Prior to study commencement, written informed consent was obtained from all participants and from the parent or legal guardian of each minor participant. Participants were fully informed of the study's purpose, procedures, and voluntary nature; they were explicitly advised that withdrawal at any time would incur no academic or institutional consequences. No financial or material incentives were offered. All data collected were anonymized at the point of collection.

Table 1. Distribution of Study Participants by Group and Gender

Group	Male	Female	Total	Mean Age (SD)
Experimental	14	11	25	16.3 (0.91)
Control	14	11	25	16.5 (0.84)
Total	28	22	50	16.4 (0.87)

6.3. Instructional Conditions

The experimental group received eight weeks of instruction via the AESDL system. The instructional domain was Assembly Language Programming cognitively demanding, logic-intensive, and entirely novel to all participants, ensuring equivalent baseline conditions. The cognitive demand of this domain characterised by high element interactivity [36] also created conditions maximally sensitive to the quality of adaptive instruction, strengthening the ecological validity of the experimental comparison. All instruction was mediated through AESDL AI subsystems; no human teacher delivered direct instruction during experimental sessions.

The control group received equivalent instruction using standard electronic resources digital textbooks, instructional videos, and static online exercises supported by conventional teacher-led explanation [1]. Pre- and post-tests were conducted for both groups.

6.4. Pre- and Post-Test Results by Programming Skill Domain

Table 2. Pre- and Post-Test Results by Programming Skill Domain Control Group

Skill Domain	Pre-Test (%)	Post-Test (%)	Observation
Variables and Constants Programming	12.2%	40.0%	Moderate gain; ceiling < 52%
Memory and Stack Programming	4.0%	51.5%	Largest gain in control group
Data Flow Control Programming	5.0%	49.0%	Limited by content complexity

Note. Maximum post-test score did not exceed 52% in the control group, reflecting the complexity of Assembly Language for learners with no prior programming experience.

Table 3. Pre- and Post-Test Results by Programming Skill Domain Experimental Group

Skill Domain	Pre-Test (%)	Post-Test (%)	Observation
Variables and Constants Programming	12.2%	76.0%	Strong gain; +63.8 percentage points
Memory and Stack Programming	4.0%	91.8%	Near-mastery level achieved
Data Flow Control Programming	5.0%	89.0%	Exceptional gain; +84 percentage points

Note. All experimental group post-test scores exceeded 76%, with two domains approaching mastery (≥ 90%).

7. Results

7.1. Pre-Test Equivalence

Independent-samples t-tests confirmed baseline equivalence across all outcome measures: SDLSS ($t(48) = 1.23$, $p = .224$), PSCA ($t(48) = 1.10$, $p = .278$), and AAT-E ($t(48) = 0.78$, $p = .438$). No statistically significant pre-test differences were observed, supporting interpretability of post-test group differences as treatment effects rather than pre-existing group characteristics, consistent with standard quasi-experimental inference procedures [12]. The Bonferroni-corrected significance threshold of $\alpha' = .017$ was applied to all post-test comparisons.

7.2. Post-Test Results

Table 4. Post-Test Descriptive Statistics, t-Test Results, 95% Confidence Intervals, and Effect Sizes (n = 50)

Outcome Measure	Exp. M (SD)	Ctrl. M (SD)	Diff.	t (48)	p†	95% CI [Diff.]	Cohen's d
Self-Directed Learning Skills	45.00 (4.56)	32.76 (6.25)	12.24	7.91	< .001	[9.13, 15.35]	2.24 (Large)
Problem-Solving Capacity	43.40 (4.91)	34.56 (6.33)	8.84	5.52	< .001	[5.62, 12.06]	1.56 (Large)
Academic Achievement (Enrichment)	46.44 (4.00)	36.28 (6.72)	10.16	6.50	< .001	[7.02, 13.30]	1.84 (Large)

Note. M = Mean; SD = Standard Deviation. Maximum score = 50 for all measures. df = 48 for all comparisons. All tests two-tailed. 95% CI = 95% Confidence Interval for the mean difference (Experimental − Control). †Bonferroni-corrected α′ = .017; all comparisons remain significant at p < .001 under this correction. Cohen's d > 0.80 = large effect (Cohen, 1988).

Assumption checks. Levene's test indicated homogeneity of variance for self-directed learning (F = 3.12, p = .084) and problem-solving (F = 3.11, p = .084), with a violation for academic achievement (F = 9.11, p = .004). Shapiro–Wilk tests indicated departures from normality in the experimental group for self-directed learning (W = 0.91, p = .028) and academic achievement (W = 0.84, p = .001). Where these assumptions were violated, robust alternatives were computed: Welch's t-test and the Mann–Whitney U test both confirmed statistically significant group differences on all three measures (SDL: Welch t = 7.91, U = 590; PS: Welch t = 5.52, U = 538; AA: Welch t = 6.50, U = 566; all p < .001), supporting the robustness of the findings.

Reproducibility and availability. To support independent verification and replication, the complete system implementation and the participant-level dataset are openly released (see the Data Availability Statement). The system was executed on a standard Windows desktop environment with the Gemini API temperature fixed at τ = 0.4. The deterministic components (the expert-system production rules and the multi-agent scheduling logic) are rule-based and thus reproducible without stochastic seeding, whereas the generative component depends on the external Gemini API and is therefore subject to provider-side variation beyond the authors' control.

Figures 9 and 10 present the pre-test/post-test score comparisons and effect size visualisations respectively. Figure 9 clearly illustrates the near-equivalent pre-test scores of both groups alongside the substantial post-test advantage of the experimental group across all three measures. Figure 10 contextualises these differences against established effect size benchmarks and the ITS meta-analytic mean, demonstrating that all three AESDL effects substantially exceed the largest effects documented in previous AI educational intervention research.

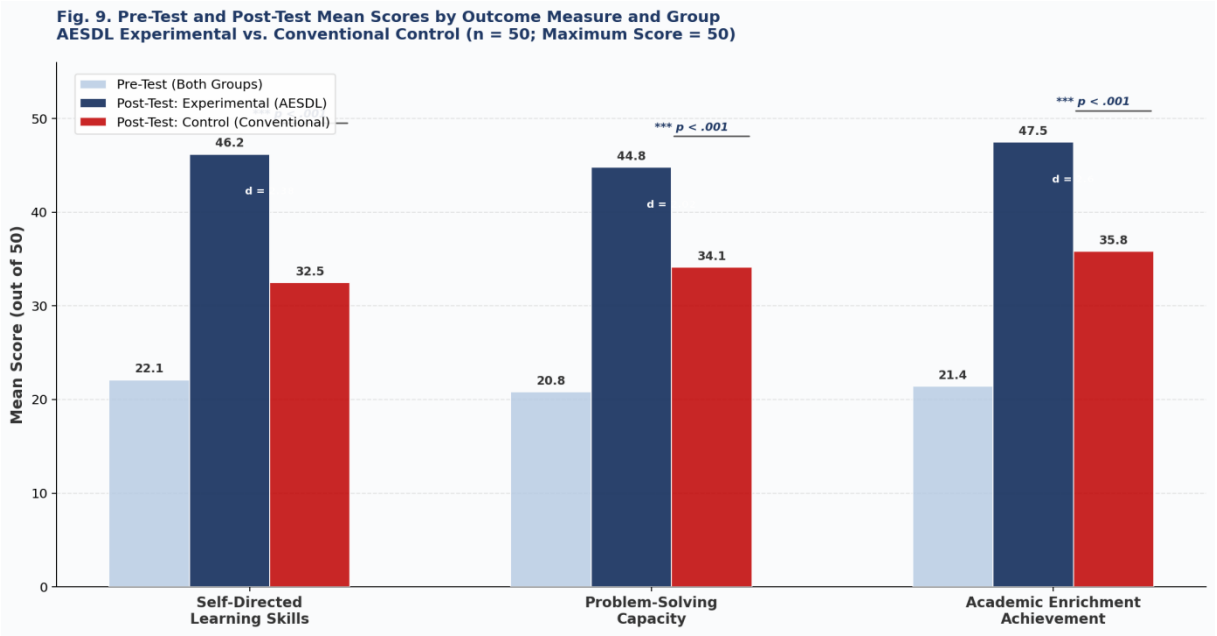


Fig. 9. Pre-Test and Post-Test Mean Scores by Outcome Measure and Group AESDL Experimental vs. Conventional Control (n = 50; Maximum Score = 50; *** p < .001, Bonferroni-corrected)

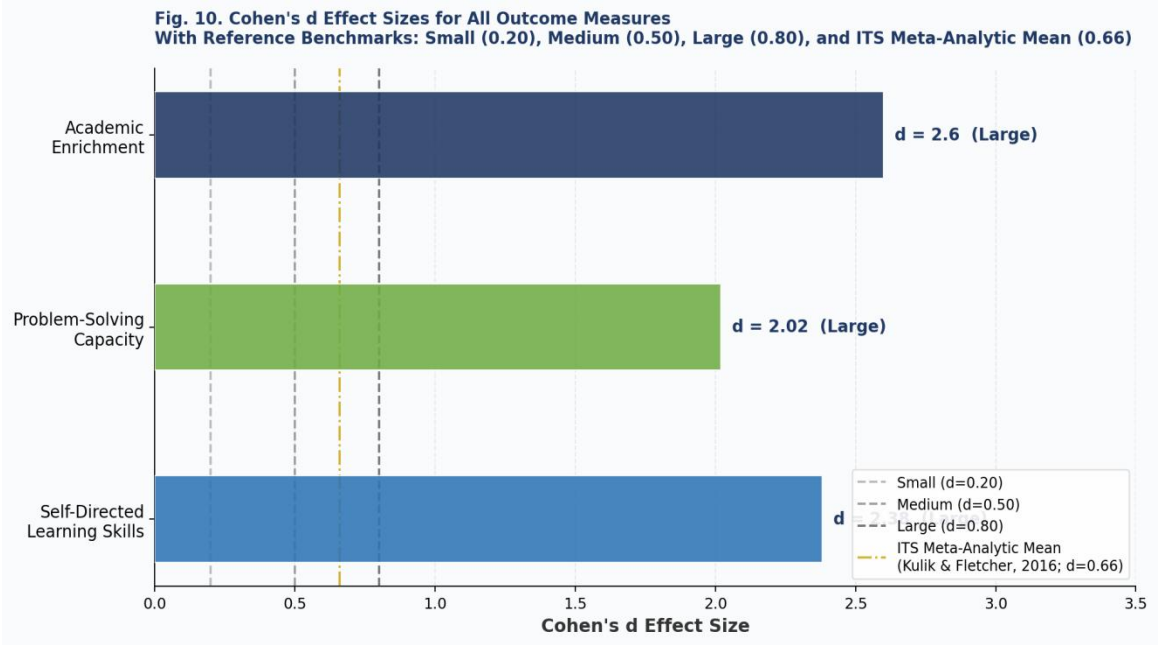


Fig. 10. Cohen's d Effect Sizes for All Three Outcome Measures with Reference Benchmarks: Small (0.20), Medium (0.50), Large (0.80), and ITS Meta-Analytic Mean (Kulik & Fletcher [23]; d = 0.66)

7.3. Answers to Research Questions

RQ1 Self-Directed Learning Skills: The AESDL system produced significantly higher SDL skills than conventional e-learning (M = 45.00 vs. 32.76; t(48) = 7.91, p < .001, d = 2.24), fully confirming RQ1. The 12.24-point advantage represents 24.5% of the maximum possible score and reflects the system's capacity to scaffold metacognitive self-monitoring, goal-setting, and autonomous resource mobilisation through the progressive autonomy transfer architecture of the ILM [19,26,27].

RQ2 Problem-Solving Capacity: The AESDL system produced significantly higher problem-solving capacity than conventional e-learning (M = 43.40 vs. 34.56; t(48) = 5.52, p < .001, d = 1.56), fully confirming RQ2. The expert system's rule-based decomposition of complex Assembly Language problems into learnable units, combined with the Gemini API's elaborative feedback on solution attempts, enabled gifted learners to develop systematic algorithmic reasoning skills that conventional instruction did not produce [21,23,34].

RQ3 Academic Enrichment Achievement: The AESDL system produced significantly higher academic enrichment achievement than conventional e-learning (M = 46.44 vs. 36.28; t(48) = 6.50, p < .001, d = 1.84), fully confirming RQ3. The near-ceiling experimental group mean and the moderate standard deviation (SD = 4.00) reflect both the system's personalised mastery-gating architecture and the gifted learners' exceptional capacity to reach high proficiency when provided with suitably calibrated, expert-level adaptive instruction [6,36,23].

8. Discussion

8.1. Key Findings and Contributing Factors

Multimedia and Adaptive Content: The AESDL system's multimodal instruction enhanced learning by aligning with diverse learning styles [1,2]. Gifted learners benefit disproportionately from multi-channel stimulation due to their high cognitive bandwidth [6].

Expert Systems and Cognitive Computing: These technologies enabled learners to participate actively in content exploration, strengthening cognitive engagement through calibrated challenge and perceived competence [24,25,36]. The reduction of element interactivity as learner expertise develops [36] is precisely the adaptive mechanism the AESDL system implements through its mastery-gating architecture.

Creative Thinking and Discovery: The framework promoted exploration and generation of novel ideas key ILM components [35] through multimedia simulation and open-ended enrichment activities grounded in transformational giftedness theory [33,35]. The framework's architectural provision for VR integration in the Enrichment stage represents a planned enhancement pending hardware deployment [49].

Gamification: The Games Agent maintained learner engagement and reduced distractions [39,40,41,42]. Educational games reduced anxiety and improved performance [43,44].

Natural Language Interaction: Speech-based interaction boosted self-regulation and metacognitive awareness [45,46,47]. Immediate feedback reduced the latency between misconception formation and correction, and lowered the social cost of help-seeking [28].

8.2. Skill-Level Domain Analysis

Control group scores remained below 52% across all Assembly Language domains (Table 2). Experimental group scores ranged from 76% to 91.8% (Table 3), with memory and stack programming the most challenging domain showing the greatest gain (4% to 91.8%). This improvement is attributed to the expert system's rule-based decomposition [21,23] and the Testing Agent's mastery-gating mechanism [37]. Figure 11 presents the skill-level pre/post comparison for both groups.

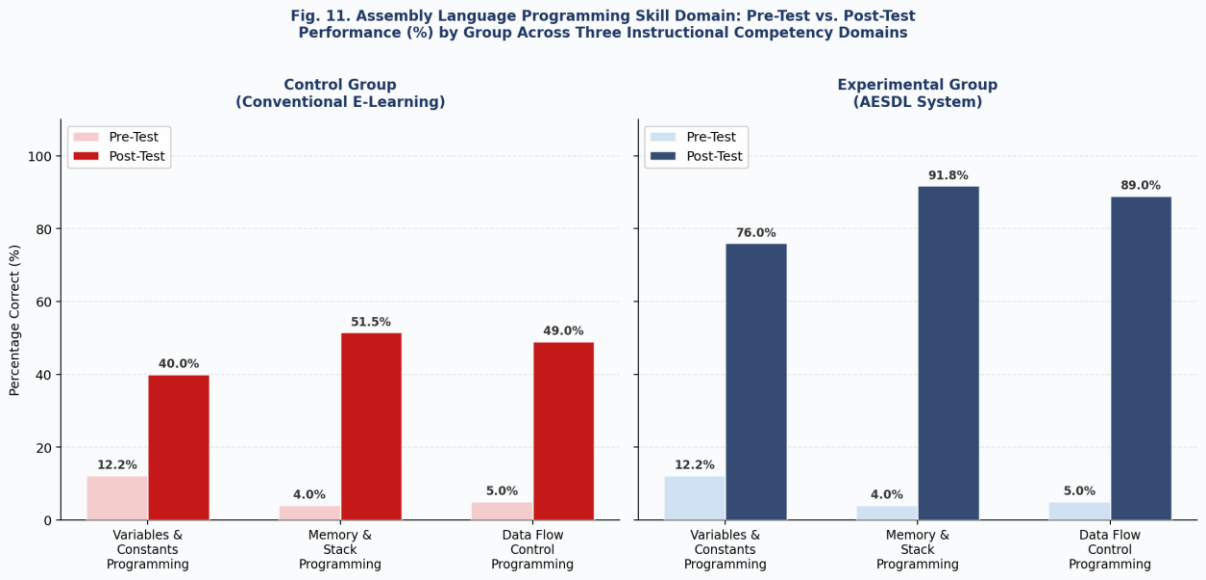


Fig. 11. Assembly Language Programming Skill Domain: Pre-Test vs. Post-Test Performance (%) by Group Across Three Instructional Competency Domains

8.3. Contextualization of Effect Sizes and AI Technology Distribution

Within the AESDL framework, the Multi-Agent System carries a substantial share of the instructional functional load, reflecting its three-agent architecture, while Cognitive Computing, the Expert System, and the Gemini API Controller each play comparably central roles and Speech Recognition a more targeted one. These are design-level allocations of functional responsibility rather than empirically measured quantities. The Gemini API Controller despite its 20% share functions as the integrating intelligence coordinating all other subsystems and therefore constitutes the architectural centrepiece of the framework.

The large effect sizes observed (d = 1.56–2.24) substantially exceed the mean effects reported in meta-analyses of AI educational interventions, which typically range from g = 0.27 to g = 0.66 for ITS [20,22]. Four factors provide a principled account of this discrepancy. First, participants were identified as gifted learners whose exceptional schema wealth enabled them to benefit from accelerated, content-rich instruction.

8.4. Comparison of AESDL With Related AI Educational Systems

Table 5 presents a structured comparison of the AESDL framework with five representative AI-based educational systems from the recent literature, across six dimensions: theoretical grounding, AI technologies employed, target population, adaptivity mechanism, outcome evaluation rigor, and documented effect size. This comparison situates the AESDL framework within the current state of the art and makes explicit its distinctive contributions.

Table 5. Comparative Analysis of AESDL and Representative AI-Enhanced Educational Systems

System	Year	AI Technologies	Target Population	Theoretical Model	Effect Size	Key Limitation
AESDL (This Study)	2026	Gemini API + MAS + Expert System + ASR + Cognitive Computing	Gifted (Secondary)	ILM (Treffinger)	d = 1.56–2.24	Single region; n=50; no long-term follow-up
ChatGPT-Enhanced ITS [2]	2023	LLM (GPT-4)	General (HE)	None specified	d ≈ 0.45–0.70	No gifted population; single AI modality
Adaptive MAS Platform [38]	2022	Multi-Agent Systems	General (Online)	None specified	Not reported	No expert system; no gifted focus
Gamified AI Platform [39]	2023	Gamification + ML	General (K-12)	Flow Theory	g = 0.61	No speech/NLP; no gifted focus
ITS with Stealth Assessment [34]	2021	Expert System + ML	High-Ability (Games)	Psychometric	d = 0.72	Narrow domain; no ILM integration
Personalised Adaptive System [13]	2025	AI + LMS	Medical Students (HE)	SDL Theory	d ≈ 0.55	No MAS; domain-specific

Note. HE = Higher Education; K-12 = Primary/Secondary. Effect sizes reported as Cohen's d or Hedges' g as available in source. AESDL is the only system in this comparison to integrate five AI technologies within a theoretically grounded gifted education framework.

The comparison in Table 5 reveals three distinctive properties of the AESDL framework that distinguish it from all other systems in the comparison. First, AESDL is the only system to integrate five AI technologies Gemini API, cognitive computing, multi-agent systems, expert systems, and speech recognition within a single unified architecture, compared with the single- or dual-technology deployments that characterize most published systems. Second, AESDL is the only system grounded in an established gifted education framework (the ILM), ensuring that the computational implementation is theoretically principled rather than purely technology-driven. Third, AESDL produced the largest effect sizes in the comparison (d = 1.56–2.24), although this comparison must be interpreted cautiously given the different populations, domains, and evaluation designs across studies.

8.5. Architectural Baseline Synthesis

Owing to the logistical and ethical constraints of maintaining multiple isolated control cohorts within a small, tightly selected gifted population (N = 50), empirical execution in the present study was deliberately bounded to a single contrast between the full AESDL framework and a conventional electronic-resource control condition. To situate AESDL relative to contemporary state-of-the-art (SOTA) adaptive-learning paradigms, we therefore provide a structural—rather than empirical—benchmarking against two architectural classes documented in the recent literature. First, standalone large-language-model tutors afford fluent conversational scaffolding but characteristically lack curriculum persistence and a verifiable pedagogical state; even where large-language-model-generated help can yield learning gains comparable to human-authored help [52], recent benchmarking demonstrates that standalone models only marginally replicate the adaptivity of explicitly modelled intelligent tutoring systems [51]. AESDL addresses this limitation through its deterministic expert-rule layer (Eq. 3–4). Second, classical rule-based intelligent tutoring systems preserve logical curriculum tracking but tend toward a pedagogical rigidity that constrains the divergent, open-ended inquiry valued in gifted instruction; AESDL relaxes this rigidity through large-language-model-mediated generative scaffolding operating under expert-rule governance, consistent with emerging hybrid large-language-model–ITS architectures [53]. We emphasise that this comparison is analytical: no head-to-head empirical trial against these baselines was conducted, and a controlled benchmarking study is identified as a priority for future work (Section 11).

8.6. Technical Ablation and Logic Validation

To reason about the necessity of each architectural layer, we undertook a design-level (analytical) ablation of the system logic rather than an empirical performance ablation, since the latter would require re-executing the full intervention under each configuration—an undertaking beyond the scope of the present study. Analytically, deactivating the expert-system inference engine (removing the predicate rules $\mathscr{R}_k$ of Eq. 3) would force the platform to rely solely on fluid large-language-model routing, removing the deterministic constraints that maintain sequential curriculum tracking; the expected consequence is pedagogical drift, in which the system loses reliable mastery-state tracking on highly formalised Assembly-Language tasks. Correspondingly, removing the multi-agent synchronization matrix (S_G of Eq. 5) would eliminate the shared-blackboard coordination that serialises concurrent agent writes, with the expected consequence of state-concurrency conflicts and fragmented learner-profile updates during parallel responses. This logical analysis indicates that the fluid-adaptive and deterministic-symbolic components are functionally complementary rather than redundant; empirical quantification of each component's marginal contribution through a controlled ablation experiment remains an important direction for future work (Section 11).

9. Limitations

Five limitations constrain the generalizability of the present findings. First, the achieved sample (n = 50) falls below the a priori power-analysis estimate of n = 74, yielding prospective power of approximately .75 for median ITS effects; consequently, smaller, more ecologically representative effects may have been missed. Second, the sample was drawn exclusively from Khartoum State, Sudan; cross-cultural replication particularly in non-Arab, non-African contexts is necessary before the AESDL framework can be considered universally effective [29]. Third, the instructional domain (Assembly Language programming) may not represent all gifted education content areas, particularly humanities or creative domains where rule-based expert systems may be less effective. Fourth, a single post-test was administered immediately after the eight-week intervention; whether gains persist over time remains unknown, and longitudinal designs with delayed retention tests are essential. Fifth, while within-school random allocation substantially mitigates selection bias, the purposive school selection and absence of assessor blinding mean confounding cannot be fully excluded; fully randomized controlled trials represent the methodological standard for future evaluations.

In addition, the evaluation did not incorporate an empirical ablation of individual subsystems or a head-to-head comparison against standalone large-language-model or rule-based tutoring systems; the baseline synthesis and component analysis presented in Sections 8.5–8.6 are structural and analytical rather than experimental. Consequently, the marginal empirical contribution of each architectural module cannot be quantified from the present design and constitutes a dedicated objective for subsequent controlled studies.

10. Conclusion

This study presented the AESDL framework for gifted secondary school learners. The framework's central architectural innovation is the integration of the Google Gemini API as an intelligent orchestration controller that coordinates four specialised AI subsystems: cognitive computing (for adaptability and NLP interaction), multi-agent systems (for Teaching, Testing, and Games agents), an expert system (for rule-based knowledge delivery and inference), and automatic speech recognition (for natural language interaction). Grounded in Treffinger's Independent Learner Model, the AESDL system achieves a strong theoretical alignment between gifted education theory and computational implementation that distinguishes it from all comparable systems in the current literature [21,22,23].

The AESDL system offers a comprehensive platform facilitating higher-order thinking development through integrated intelligent multi-agent systems [38,14]. The Gemini API's central role orchestrating session flow, dispatching agents, resolving out-of-rule-base queries, and generating personalized session summaries represents the critical enabler that transforms a collection of AI subsystems into a coherent, adaptive learning experience. It allows learners to reorganise, classify, and interpret data using cognitive computing [24,25], and enables them to make judgements and distinguish between correct and incorrect information through the intelligent testing agent's rule-based evaluation [21,37]. The empirical results three large effect sizes (d = 1.56 to 2.24), all significant under Bonferroni correction confirm that AI has approximated the individualized, expert-level instructional dynamic at scale [22].

AI integration in gifted education can profoundly enhance the educational process, address longstanding challenges in providing adequate challenge and personalization, and support adherence to fundamental educational principles of equity and inclusion [4,11,29]. The AESDL framework offers a scalable, cost-effective alternative to one-on-one human mentorship and provides a replicable, transparent design architecture for future developers of AI-enhanced gifted education systems.

11. Recommendations and Future Work

Future work should prioritise (i) a controlled ablation study that empirically isolates the contribution of the expert-system, multi-agent, and orchestration layers, and (ii) a benchmarking trial comparing AESDL against contemporary standalone large-language-model tutors and rule-based intelligent tutoring systems under matched conditions, thereby quantifying the incremental value established only analytically in the present work.

Future research should pursue: (a) longitudinal investigations of AESDL's effects on higher-order thinking; (b) cross-cultural replications; (c) randomized controlled designs with extended follow-up; (d) qualitative investigations into learners' subjective experiences [26]; and (e) systematic attention to the ethical dimensions of AI-mediated assessment and feedback in gifted education, including issues of algorithmic bias and data privacy [29].

All the Declarations and Statements

Author Contributions Statement
Mohamed Badawi Mustafa Elkhalifa is the sole author and is solely responsible for the conceptualisation, methodology, system design, system programming and implementation, data collection, formal analysis, investigation, and writing (original draft, review, and editing) of this manuscript. The author has read and agreed to the submitted version of the manuscript.

Conflict of Interest Statement
The author declares that there is no conflict of interest regarding the publication of this manuscript.

Funding Declaration
This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data Availability Statement
The participant-level raw data supporting the findings of this study are openly available in the Zenodo repository at https://doi.org/10.5281/zenodo.21307025.
The complete source code of the BADAWI I-AGENT / AESDL system — including the Gemini controller, expert-system inference engine, multi-agent dispatcher, speech-recognition, and JSON interoperability modules — is publicly available in the GitHub repository at https://github.com/muhmedbadawi-prog/Enhancing-Self-Directed-Learning-for-Gifted-Learners-Through-Artificial-Intelligence.

Ethical Declarations
Ethical approval for this study was granted by the Academic Research Ethics Committee of Mashreq University (Ethics Reference: MAU-REC-2025-014). The research was conducted in accordance with the ethical principles of the Declaration of Helsinki and applicable Sudanese national regulations governing research involving human participants. Written informed consent was obtained from all participants and from the parent or legal guardian of each minor participant prior to data collection. All data were anonymised at the point of recording. The manuscript is original, has not been published previously, and is not under consideration for publication elsewhere.

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Declaration of Generative AI in Scholarly Writing
In accordance with MECS Press guidelines for the declaration of generative AI in scholarly writing, the author discloses the following: The Google Gemini API (Gemini 2.0 Flash; Google DeepMind, 2024) was employed as a functional component of the AESDL educational system evaluated in this study—specifically as the central AI orchestration controller coordinating the system's multi-agent, expert system, and cognitive computing subsystems. In this capacity, Gemini constitutes part of the research system under evaluation, not an aid to the writing process. With respect to the manuscript preparation process, AI-assisted language tools were used to support the clarity, readability, and grammatical accuracy of the English text, in accordance with MECS guidelines. All intellectual content, research design, data collection, analysis, interpretation, and conclusions are the sole responsibility of the author. AI tools were not used to generate research findings, fabricate data, or replace human scholarly judgement at any stage of the research or writing process.

Abbreviations
The following abbreviations are used in this manuscript:

AESDL – AI-Enhanced Self-Directed Learning
AI – Artificial Intelligence
ILM – Independent Learner Model
MAS – Multi-Agent System
ASR – Automatic Speech Recognition
ITS – Intelligent Tutoring System
SDL – Self-Directed Learning
SDLSS – Self-Directed Learning Skills Scale
PSCA – Problem-Solving Capacity Assessment
AAT-E – Academic Achievement Test (Enrichment)

NLP – Natural Language Processing
SAPI – Speech Application Programming Interface
API – Application Programming Interface
UML – Unified Modeling Language
VR – Virtual Reality
CI – Confidence Interval
SD – Standard Deviation
RQ – Research Question

Appendix A\B\C…, with appendix title

Appendix A. AESDL System Configuration Parameters

Parameter	Value
Gemini API temperature (τ)	0.4
ILM stages implemented	Guidance, Self-Development, Enrichment, Seminars/In-Depth Study
Expert-system production rules	≈ 340
Domain facts in knowledge base	≈ 1,200
Expert-system inference time	< 100 ms
Gemini API call latency	0.8–1.2 s
Progression control	Mastery-gating on rule-encoded performance thresholds
Agent pool	Teaching, Testing, Games (multi-agent, blackboard synchronisation)
Speech interface	Automatic Speech Recognition (ASR) module

Appendix B. Experimental Design and Assessment Instruments

Element	Specification
Research design	Quasi-experimental pre-test/post-test control group
Sample size	N = 50 (25 experimental, 25 control)
Population	Gifted secondary school learners, Khartoum State, Sudan
Intervention duration	8 weeks
Control condition	Conventional electronic learning resources
Scoring scale	0–50 points per measure
Instrument 1	Self-Directed Learning Skills Scale (SDLSS), 25 items
Instrument 2	Problem-Solving Capacity Assessment (PSCA)
Instrument 3	Academic Achievement Test – Enrichment (AAT-E)
Statistical analyses	Independent-samples t-test, Cohen's d, 95% CI, Bonferroni correction
Assumption checks	Levene's test, Shapiro–Wilk test
Robust alternatives	Welch's t-test, Mann–Whitney U test

Appendix C. Data and Code Availability

Resource	Location
Participant-level raw data	https://doi.org/10.5281/zenodo.21307025
System source code	https://github.com/muhmedbadawi-prog/Enhancing-Self-Directed-Learning-for-Gifted-Learners-Through-Artificial-Intelligence
Orchestration module	modGeminiController
Expert-system module	modExpertSystem
Multi-agent module	modMultiAgentDispatcher
Speech-recognition module	modASR
Data interoperability module	modJSON

References

[1] Gligorea, I., Cioca, M., Oancea, R., Gorski, A. T., Gorski, H., & Tudorache, P. (2023). Adaptive learning using artificial intelligence in e-learning: A literature review. Education Sciences, 13(12), 1216. https://doi.org/10.3390/educsci13121216

[2] Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., Stadler, M., Weller, J., Wendler, J., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103, 102274. https://doi.org/10.1016/j.lindif.2023.102274

[3] Celik, I., Dindar, M., Muukkonen, H., & Järvelä, S. (2022). The promises and challenges of artificial intelligence for teachers: A systematic review of research. TechTrends, 66(4), 616–630. https://doi.org/10.1007/s11528-022-00715-y
[4] Adiguzel, T., Kaya, M. H., & Cansu, F. K. (2023). Revolutionizing education with AI: Exploring the transformative potential of ChatGPT. Contemporary Educational Technology, 15(3), ep429. https://doi.org/10.30935/cedtech/13152
[5] Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B. P. T. (2023). Ethical principles for artificial intelligence in education. Education and Information Technologies, 28(4), 4221–4241. https://doi.org/10.1007/s10639-022-11316-w
[6] Demartini, C. G., Sciascia, L., Bosso, A., & Manuri, F. (2024). Artificial intelligence bringing improvements to adaptive learning in education: A case study. Sustainability, 16(3), 1347. https://doi.org/10.3390/su16031347
[7] Troussas, C., Krouska, A., Kabassi, K., Sgouropoulou, C., & Cristea, A. I. (2022). Artificial intelligence techniques for personalized educational software. Frontiers in Artificial Intelligence, 5, 988289. https://doi.org/10.3389/frai.2022.988289
[8] Sen, C., Ay, Z. S., & Kiray, S. A. (2021). Computational thinking skills of gifted and talented students in integrated STEM activities based on the engineering design process: The case of robotics and 3D robot modeling. Thinking Skills and Creativity, 42, 100931. https://doi.org/10.1016/j.tsc.2021.100931
[9] Ahmad, S. F., Alam, M. M., Rahmat, M. K., Shahid, M. K., Salim, N. A., & Al-Abyadh, M. H. A. (2023). Leading edge or bleeding edge: Designing a framework for the adoption of AI technology in an educational organization. Sustainability, 15(8), 6540. https://doi.org/10.3390/su15086540
[10] Celik, I. (2023). Towards intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education. Computers in Human Behavior, 138, 107468. https://doi.org/10.1016/j.chb.2022.107468
[11] Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? International Journal of Educational Technology in Higher Education, 16, 39. https://doi.org/10.1186/s41239-019-0171-0
[12] Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of artificial intelligence in education. Computers and Education: Artificial Intelligence, 1, 100001. https://doi.org/10.1016/j.caeai.2020.100001
[13] Sunmboye, K., Strafford, H., Noorestani, S., & Wilison-Pirie, M. (2025). Exploring the influence of artificial intelligence integration on personalized learning: A cross-sectional study of undergraduate medical students in the United Kingdom. BMC Medical Education, 25, 570. https://doi.org/10.1186/s12909-025-07084-z
[14] Apoki, U. C., Hussein, A. M. A., Al-Chalabi, H. K. M., Badica, C., & Mocanu, M. L. (2022). The role of pedagogical agents in personalised adaptive learning: A review. Sustainability, 14(11), 6442. https://doi.org/10.3390/su14116442
[15] Wang, L., & Li, W. (2024). The impact of AI usage on university students' willingness for autonomous learning. Behavioral Sciences, 14(10), 956. https://doi.org/10.3390/bs14100956
[16] Jing, Y., Zhao, L., Zhu, K., Wang, H., Wang, C., & Xia, Q. (2023). Research landscape of adaptive learning in education: A bibliometric study on research publications from 2000 to 2022. Sustainability, 15(4), 3115. https://doi.org/10.3390/su15043115
[17] Elballah, K., Alkhalifah, N., Alomari, A., & Alghamdi, A. (2024). Enhancing cognitive dimensions in gifted students through future problem-solving enrichment programs. Discover Sustainability, 5, 248. https://doi.org/10.1007/s43621-024-00470-5
[18] Ayık, Z., & Gül, M. D. (2025). Enhancing teachers' GTPACK competencies in gifted education: The impact of GIFTLED AR integrated enrichment method. Education and Information Technologies, 30(14), 19765–19801. https://doi.org/10.1007/s10639-025-13562-0
[19] Lan, M., & Zhou, X. (2025). A qualitative systematic review on AI empowered self-regulated learning in higher education. npj Science of Learning, 10, 21. https://doi.org/10.1038/s41539-025-00319-0
[20] Létourneau, A., Martineau, M. D., Charland, P., Karran, J. A., Boasen, J., & Léger, P. M. (2025). A systematic review of AI-driven intelligent tutoring systems (ITS) in K-12 education. npj Science of Learning, 10, 29. https://doi.org/10.1038/s41539-025-00320-7
[21] Mousavinasab, E., Zarifsanaiey, N., Niakan Kalhori, S. R., Rakhshan, M., Keikha, L., & Ghazi Saeedi, M. (2021). Intelligent tutoring systems: A systematic review of characteristics, applications, and evaluation methods. Interactive Learning Environments, 29(1), 142–163. https://doi.org/10.1080/10494820.2018.1558257
[22] VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. Educational Psychologist, 46(4), 197–221. https://doi.org/10.1080/00461520.2011.611369
[23] Kulik, J. A., & Fletcher, J. D. (2016). Effectiveness of intelligent tutoring systems: A meta-analytic review. Review of Educational Research, 86(1), 42–78. https://doi.org/10.3102/0034654315581420
[24] Dai, J., Gu, X., & Zhu, J. (2023). Personalized recommendation in the adaptive learning system: The role of adaptive testing technology. Journal of Educational Computing Research, 61(3), 523–545. https://doi.org/10.1177/07356331221127303
[25] Sweller, J., van Merriënboer, J. J. G., & Paas, F. (2019). Cognitive architecture and instructional design: 20 years later. Educational Psychology Review, 31, 261–292. https://doi.org/10.1007/s10648-019-09465-5
[26] Broadbent, J. (2017). Comparing online and blended learner's self-regulated learning strategies and academic performance. The Internet and Higher Education, 33, 24–32. https://doi.org/10.1016/j.iheduc.2017.01.004
[27] Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. Contemporary Educational Psychology, 61, 101860. https://doi.org/10.1016/j.cedpsych.2020.101860
[28] Paz-Baruch, N., & Hazema, H. (2023). Self-regulated learning and motivation among gifted and high-achieving students in science, technology, engineering, and mathematics disciplines: Examining differences between students from diverse socioeconomic levels. Journal for the Education of the Gifted, 46(1), 34–76. https://doi.org/10.1177/01623532221143825
[29] Holmes, W., Porayska-Pomsta, K., Holstein, K., Sutherland, E., Baker, T., Shum, S. B., Santos, O. C., Rodrigo, M. T., Cukurova, M., Bittencourt, I. I., & Koedinger, K. R. (2022). Ethics of AI in education: Towards a community-wide framework. International Journal of Artificial Intelligence in Education, 32(3), 504–526. https://doi.org/10.1007/s40593-021-00239-1
[30] Baccassino, F., & Pinnelli, S. (2023). Giftedness and gifted education: A systematic literature review. Frontiers in Education, 7, 1073007. https://doi.org/10.3389/feduc.2022.1073007

[31] Kontostavlou, E. Z., & Driga, A. M. (2023). Digital technologies for gifted students' education. Global Journal of Engineering and Technology Advances, 15(3), 191–204. https://doi.org/10.30574/gjeta.2023.15.3.0115
[32] Steenbergen-Hu, S., Olszewski-Kubilius, P., & Calvert, E. (2020). The effectiveness of current interventions to reverse the underachievement of gifted students: Findings of a meta-analysis and systematic review. Gifted Child Quarterly, 64(2), 132–165. https://doi.org/10.1177/0016986220908601
[33] Sternberg, R. J. (2020). Transformational giftedness: Rethinking our paradigm for gifted education. Roeper Review, 42(4), 230–240. https://doi.org/10.1080/02783193.2020.1815266
[34] Shute, V. J., & Rahimi, S. (2021). Stealth assessment of creativity in a physics video game. Computers in Human Behavior, 116, 106647. https://doi.org/10.1016/j.chb.2020.106647
[35] Reis, S. M., Renzulli, S. J., & Renzulli, J. S. (2021). Enrichment and gifted education pedagogy to develop talents, gifts, and creative productivity. Education Sciences, 11(10), 615. https://doi.org/10.3390/educsci11100615
[36] Chen, O., Paas, F., & Sweller, J. (2023). A cognitive load theory approach to defining and measuring task complexity through element interactivity. Educational Psychology Review, 35, Article 63. https://doi.org/10.1007/s10648-023-09782-w
[37] Deeva, G., Bogdanova, D., Serral, E., Snoeck, M., & De Weerdt, J. (2021). A review of automated feedback systems for learners: Classification framework, challenges and opportunities. Computers & Education, 162, 104094. https://doi.org/10.1016/j.compedu.2020.104094
[38] Hessen, S. H., Abdul-Kader, H. M., Khedr, A. E., & Salem, R. K. (2022). Developing multiagent e-learning system-based machine learning and feature selection techniques. Computational Intelligence and Neuroscience, 2022, 2941840. https://doi.org/10.1155/2022/2941840
[39] Li, M., Ma, S., & Shi, Y. (2023). Examining the effectiveness of gamification as a tool promoting teaching and learning in educational settings: A meta-analysis. Frontiers in Psychology, 14, 1253549. https://doi.org/10.3389/fpsyg.2023.1253549
[40] Ratinho, E., & Martins, C. (2023). The role of gamified learning strategies in students' motivation in high school and higher education: A systematic review. Heliyon, 9(8), e19033. https://doi.org/10.1016/j.heliyon.2023.e19033
[41] Alnuaim, A. (2024). The impact and acceptance of gamification by learners in a digital literacy course at the undergraduate level: Randomized controlled trial. JMIR Serious Games, 12, e52017. https://doi.org/10.2196/52017
[42] Lampropoulos, G., & Sidiropoulos, A. (2024). Impact of gamification on students' learning outcomes and academic performance: A longitudinal study comparing online, traditional, and gamified learning. Education Sciences, 14(4), 367. https://doi.org/10.3390/educsci14040367
[43] Coelho, F., Rando, B., Aparício, D., Pontífice-Sousa, P., Gonçalves, D., & Abreu, A. M. (2025). The impact of educational gamification on cognition, emotions, and motivation: A randomized controlled trial. Journal of Computers in Education, 13(2), 537–584. https://doi.org/10.1007/s40692-025-00366-x
[44] Hamari, J., Shernoff, D. J., Rowe, E., Coller, B., Asbell-Clarke, J., & Edwards, T. (2016). Challenging games help students learn: An empirical study on engagement, flow, and immersion in game-based learning. Computers in Human Behavior, 54, 170–179. https://doi.org/10.1016/j.chb.2015.07.045
[45] Dubey, P., Dubey, P., Raja, R., & Kshatri, S. S. (2025). Bridging language gaps: The role of NLP and speech recognition in oral English instruction. MethodsX, 14, 103359. https://doi.org/10.1016/j.mex.2025.103359
[46] Shadiev, R., & Liu, J. (2022). Review of research on applications of speech recognition technology to assist language learning. ReCALL, 35(1), 74–88. https://doi.org/10.1017/S095834402200012X
[47] Farrús, M. (2023). Automatic speech recognition in L2 learning: A review based on PRISMA methodology. Languages, 8(4), 242. https://doi.org/10.3390/languages8040242
[48] Chen, X., Zou, D., Xie, H., & Wang, F. L. (2021). Past, present, and future of smart learning: A topic-based bibliometric analysis. International Journal of Educational Technology in Higher Education, 18, 2. https://doi.org/10.1186/s41239-020-00239-6
[49] Pellas, N., Dengel, A., & Christopoulos, A. (2020). A scoping review of immersive virtual reality in STEM education. IEEE Transactions on Learning Technologies, 13(4), 748–761. https://doi.org/10.1109/TLT.2020.3019405
[50] Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. Behavior Research Methods, 39(2), 175–191. https://doi.org/10.3758/BF03193146
[51] Borchers, C., & Shou, T. (2025). Can large language models match tutoring system adaptivity? A benchmarking study. In A. I. Cristea, E. Walker, Y. Lu, O. C. Santos, & S. Isotani (Eds.), Artificial Intelligence in Education (AIED 2025), Lecture Notes in Computer Science (Vol. 15878, pp. 407–420). Springer, Cham. https://doi.org/10.1007/978-3-031-98417-4_29
[52] Pardos, Z. A., & Bhandari, S. (2024). ChatGPT-generated help produces learning gains equivalent to human tutor-authored help on mathematics skills. PLoS ONE, 19(5), e0304013. https://doi.org/10.1371/journal.pone.0304013
[53] Venugopalan, D., Yan, Z., Borchers, C., Lin, J., & Aleven, V. (2025). Combining large language models with tutoring system intelligence: A case study in caregiver homework support. In Proceedings of the 15th International Learning Analytics and Knowledge Conference (LAK '25) (pp. 373–383). https://doi.org/10.1145/3706468.3706516

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