

GENERATIVE AI-BASED ADAPTIVE METHODOLOGY FOR INFORMATICS EDUCATION: RELIABILITY AND EDUCATIONAL EFFECTIVENESS ANALYSIS

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Abstract: Artificial Intelligence (AI) technologies are rapidly transforming modern education, creating new opportunities for adaptive and differentiated learning. This study proposes a generative AI-based methodological framework for developing differentiated educational tasks in secondary school informatics education. The methodology integrates competency-based educational standards, conceptual curriculum node architecture (CCN), and natural language processing (NLP) technologies to automatically generate educational content aligned with students' knowledge levels. The proposed framework was developed based on the state educational standards for Informatics and Information Technologies in Uzbekistan, particularly focusing on A2 and A2+ competency levels.

The research introduces a structured pipeline that connects curriculum concepts, terminological dictionaries, practical assignments, and assessment tasks with generative AI systems. Experimental implementation was conducted for Grade 9 informatics topics, including computer systems and operating systems. The results demonstrate that AI-generated tasks can support differentiated instruction, improve content personalization, and maintain methodological consistency with curriculum requirements. The study concludes that generative AI can significantly enhance adaptive learning environments while preserving pedagogical reliability and competency-oriented educational objectives. The study concludes that generative AI can significantly enhance adaptive learning environments while preserving pedagogical reliability and competency-oriented educational objectives.

Keywords: Generative Artificial Intelligence, Adaptive Learning, Informatics Education, Natural Language Processing, Differentiated Instruction, Competency-Based Education, Educational Technology, Prompt Engineering, Semantic Curriculum Mapping, Reliability Analysis

INTRODUCTION

The rapid development of artificial intelligence technologies has significantly transformed modern educational systems, particularly through the emergence of Generative Artificial Intelligence (Generative AI) and NLP technologies. Generative AI systems are increasingly being integrated into educational environments to support adaptive learning, intelligent tutoring, automated assessment, and personalized educational content generation. These technologies enable the creation of dynamic instructional materials adapted to learners' cognitive abilities, competency levels, and educational needs. As a result, Generative AI has become one of the most promising directions in educational technology research.

In secondary school informatics education, differentiated instruction is especially important because students demonstrate substantial differences in digital literacy, logical reasoning, algorithmic thinking, computational problem-solving, and programming skills. Traditional uniform teaching approaches often fail to address these differences effectively. Consequently, many learners either experience insufficient academic challenge or encounter difficulties in

mastering educational content that does not correspond to their competency level. Preparing differentiated educational materials manually requires considerable pedagogical expertise, methodological planning, and additional instructional time, creating substantial workload challenges for teachers. Modern competency-based educational systems require adaptive methodologies capable of generating instructional materials aligned with different learner profiles. In Uzbekistan, the State Educational Standards for Informatics and Information Technologies define competency-oriented educational levels such as A1, A2, and B1, focusing on information processing, algorithmic thinking, programming, digital technologies, and information security competencies. However, practical implementation of competency-based differentiated instruction remains methodologically complex within real classroom environments.

Recent advances in Generative AI and NLP technologies provide new opportunities for addressing these challenges through automated educational content generation. Large language models and AI-driven educational systems are capable of analyzing curriculum structures, competency requirements, and conceptual relationships in order to generate adaptive learning materials automatically. Nevertheless, several critical challenges remain unresolved, including pedagogical reliability, curriculum alignment, conceptual consistency, and educational validity of AI-generated materials. This research proposes a Generative AI-based adaptive methodology for differentiated educational task generation in secondary school informatics education. The study introduces an integrated instructional framework combining competency-based curriculum standards, CCN architecture, differentiated educational levels, terminological dictionaries, and NLP-driven generative mechanisms into a unified pedagogical model for Grade 9 Informatics education.

LITERATURE REVIEW

Recent advances in Generative Artificial Intelligence (Generative AI) have significantly influenced educational technology research, particularly in adaptive learning, automated content generation, intelligent tutoring systems, and personalized instructional environments. Researchers increasingly emphasize the ability of Generative AI systems to support differentiated instruction through NLP, semantic analysis, and automated educational content generation mechanisms.

Mittal, Sai, Chamola, and Sangwan [1] conducted a comprehensive review of Generative AI applications in education and analyzed the role of generative models in adaptive learning environments. The authors highlighted the capability of Generative AI systems to automatically generate instructional texts, images, videos, and personalized learning resources according to students' learning preferences and competency profiles. Their study also examined conversational educational interfaces and emphasized the importance of addressing challenges related to data privacy, algorithmic bias, and accountability in AI-driven educational systems. Alasadi and Baiz [2] investigated the opportunities and challenges associated with integrating Generative AI technologies into education and scientific research. Their work focused on ethical concerns, accessibility issues, academic integrity, and responsible AI usage in educational environments. The authors emphasized that while Generative AI can substantially improve educational efficiency and content accessibility, human supervision and ethical guidelines remain essential for reliable implementation. Noroozi et al. [3] explored pedagogical, theoretical, and methodological perspectives of Generative AI in education, particularly focusing on ChatGPT and large language models. The authors analyzed multiple educational studies demonstrating that Generative AI systems can improve learner engagement, personalized feedback, language learning, and educational research processes. At the same time, the study highlighted challenges associated with

contextual understanding, critical thinking development, privacy risks, and the necessity of human-centered AI governance in education.

Zapata-Rivera et al. [4] examined the transformative role of Generative AI in educational systems and discussed its application in intelligent tutoring, personalized assessment, AI-based mentoring, automated feedback generation, and interactive learning environments. Their study demonstrated that large language models can dynamically adapt instructional materials according to learner proficiency, learning pace, and educational needs. The authors also emphasized the importance of emotional and pedagogical aspects in AI-generated tutoring systems. Liu et al. [5] investigated the practical implementation of Generative AI technologies in Harvard University's CS50 computer science course. The researchers developed AI-based educational tools capable of explaining code fragments, supporting programming tasks, and answering curricular questions in real time. Their findings demonstrated that AI-assisted instructional systems can approximate personalized tutoring environments and improve the effectiveness of computer science education through continuous adaptive support mechanisms. Franklin et al. [6] analyzed the impact of Generative AI technologies on computer science education and discussed both the opportunities and challenges associated with AI-assisted programming instruction. The authors emphasized that Generative AI lowers technical barriers in programming education and supports computational problem-solving activities. However, they also identified important concerns regarding assessment validity, academic integrity, and the changing nature of programming assignments in AI-supported educational environments.

Lee and Song [7] explored teachers' and students' perceptions of AI-generated conceptual explanations in computer science education. Their research compared educational explanations generated by teachers and ChatGPT for programming concepts such as sequence, selection, and iteration. The study revealed that Generative AI-generated explanations were often perceived as pedagogically useful and understandable, although differences remained between teacher-oriented and student-oriented evaluation criteria. The authors concluded that AI literacy and pedagogical adaptation are necessary for effective integration of Generative AI into computer science instruction. Zimmermann, Janetzko, and Haymond [8] investigated strategies for integrating Generative AI methods into computer science education from both student and lecturer perspectives. Their study demonstrated that Generative AI systems can support coding assistance, algorithm explanation, writing improvement, computational modeling, and problem-solving skill development. The authors proposed that responsible integration of Generative AI technologies can improve analytical thinking, creativity, and adaptive learning processes within computer science education.

Although previous studies extensively investigated Generative AI applications in education, several important limitations remain insufficiently addressed. Existing research primarily focuses on general educational adaptation, tutoring systems, or programming assistance tools, while relatively limited attention has been devoted to competency-oriented differentiated educational content generation aligned with formal state educational standards. In addition, many studies lack structured semantic curriculum architectures capable of preserving pedagogical consistency, competency alignment, and conceptual coherence during automated educational generation.

Therefore, this research extends previous studies by proposing a curriculum-aligned Generative AI framework integrating competency-based educational standards, Conceptual Curriculum Node semantic mapping, NLP-driven educational generation mechanisms,

differentiated instructional structures, and pedagogical validation procedures for secondary school informatics education.

METHODOLOGY

1.1 Research Design

This research employed a mixed-method methodology integrating instructional design principles, NLP-driven generative modeling, semantic curriculum mapping, and pedagogical reliability analysis. Unlike previous adaptive instructional models primarily focused on learner diagnostics and assessment adaptation, the proposed methodology concentrated on automated differentiated educational content generation through Generative AI technologies.

The methodological framework was implemented for Grade 9 Informatics education using competency-oriented curriculum materials aligned with Uzbekistan's national educational standards. The study focused specifically on constructing a curriculum-constrained generative architecture capable of producing adaptive educational materials according to differentiated learner competency levels. The proposed methodology integrated semantic curriculum parsing, CCN unified AI-driven educational generation pipeline. This approach enabled automated generation of theoretical questions, practical assignments, competency-oriented assessment tasks, and instructional guidance while preserving curriculum alignment and pedagogical consistency.

1.2 Educational Standards Integration

The methodological foundation of the proposed framework was based on competency-oriented educational standards for Informatics and Information Technologies education. The system incorporated A2 and A2+ competency requirements together with differentiated A-, B-, and C-level instructional structures corresponding to varying learner proficiency and cognitive complexity levels. Unlike conventional educational generation approaches based on unrestricted prompts, the proposed methodology transformed curriculum competencies into structured AI-readable semantic representations. Competency categories related to information processing, algorithmic thinking, software usage, digital communication, and electronic data management were encoded into semantic instructional structures guiding the generative AI system during educational content production. This competency-mapping mechanism enabled the AI framework to preserve curriculum alignment and instructional consistency during automated task generation. The resulting semantic architecture reduced conceptual inconsistency and improved adaptive correspondence between generated educational materials and targeted competency outcomes.

1.3 CCN-Based Curriculum Architecture

The study introduced a Conceptual Curriculum Node architecture functioning as a semantic curriculum representation model for Generative AI-based educational generation. Unlike traditional topic-based instructional structures, the proposed CCN framework organized curriculum content through interconnected semantic educational nodes containing conceptual definitions, competency targets, terminological dictionaries, theoretical questions, practical assignments, and instructional relationships. The CCN structure was implemented using structured JSON-based educational representations that enabled machine-readable semantic curriculum parsing and adaptive content generation. Example CCN nodes included hardware and software systems, CPU and memory architecture, operating systems, GUI and CLI interfaces, file hierarchy structures, and driver management concepts.

The proposed semantic architecture established structured relationships between curriculum concepts, learner competency levels, and instructional objectives. This framework enabled the generative AI system to construct differentiated educational materials while

preserving conceptual coherence, competency alignment, and pedagogical consistency throughout the content generation process.

Figure 1. SPGF Architecture for Generative AI-Based Differentiated Informatics Education

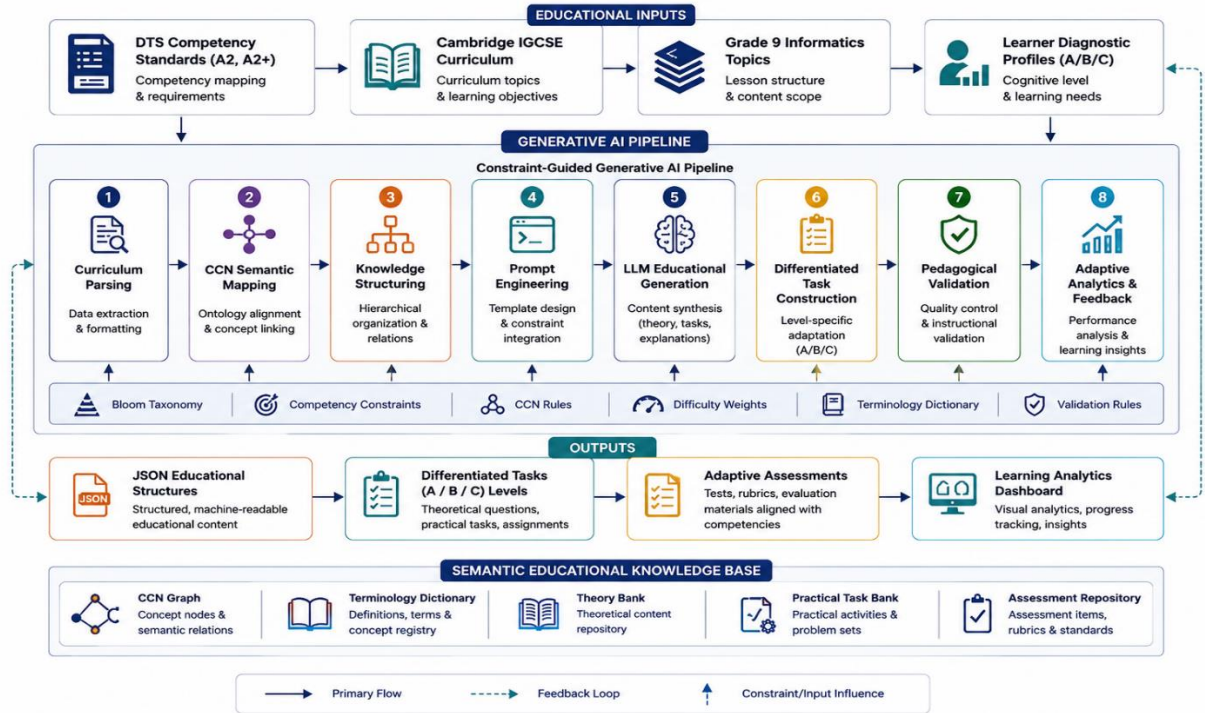


Figure 1. SPGF Architecture for Generative AI-Based Differentiated Informatics Education

The architecture presented in Figure 1 illustrates the interaction between curriculum constraints, semantic educational mapping, prompt engineering mechanisms, and adaptive NLP-based educational generation layers. The SPGF framework establishes a closed-loop instructional pipeline in which competency-oriented educational standards directly influence differentiated content generation, pedagogical validation, and adaptive assessment structures. The integration of semantic control layers and validation feedback mechanisms reduces conceptual inconsistency during AI-based educational synthesis while preserving curriculum alignment across multiple learner competency levels.

1.4 Differentiated Learning Structure

Educational content was generated according to three differentiated learner categories corresponding to varying competency levels and cognitive complexity. The C level focused primarily on conceptual recognition, terminology identification, and foundational understanding tasks. The B level emphasized conceptual explanation, comparison, interpretation, and intermediate analytical activities. In contrast, the A level targeted higher-order reasoning, situational analysis, adaptive problem-solving, and competency-oriented decision-making tasks. Unlike conventional static instructional models, the proposed Generative AI framework dynamically generated differentiated theoretical questions, practical assignments, assessment tasks, and instructional guidance according to semantic curriculum constraints and learner-level requirements. The adaptive generation process integrated competency mapping, CCN semantic relationships, and prompt engineering mechanisms to preserve instructional coherence across multiple educational levels.

The proposed methodology introduced a curriculum-constrained generative educational architecture in which AI-generated content remained semantically aligned with predefined competency objectives, conceptual dependencies, and pedagogical requirements. This structure

reduced uncontrolled educational generation and improved the reliability and instructional validity of differentiated educational materials. As illustrated in Figure 1, the proposed framework integrates competency-oriented educational standards, semantic curriculum mapping, CCN architecture, prompt engineering, and NLP-driven generative AI mechanisms into a unified adaptive instructional pipeline. The architecture supports automated differentiated educational content generation while maintaining curriculum consistency, semantic coherence, and pedagogical reliability across multiple learner competency levels.

1.5 Generative AI Pipeline Implementation

The proposed SPGF framework employed a constraint-guided generative AI pipeline designed to produce differentiated educational materials aligned with competency-oriented instructional objectives. Unlike unrestricted large language model generation approaches, the proposed methodology integrated semantic curriculum structures, CCN, competency mappings, and prompt engineering mechanisms into a controlled educational generation environment.

At the initial stage, curriculum documents, competency standards, terminological dictionaries, and lesson structures were transformed into structured JSON-based educational representations. These representations contained semantic relationships between curriculum concepts, learner competency levels, educational objectives, theoretical components, and practical activities. The structured architecture enabled machine-readable curriculum interpretation and adaptive educational generation. The generative pipeline subsequently applied CCN-based semantic mapping procedures to establish conceptual dependencies between educational topics and competency-oriented learning outcomes. Each curriculum node included conceptual definitions, prerequisite relationships, theoretical explanations, practical assignments, and differentiated instructional constraints associated with A-, B-, and C-level learner categories.

Prompt engineering mechanisms played a central role in controlling AI-generated educational content. The prompts incorporated competency constraints, Bloom's taxonomy levels, semantic curriculum rules, learner-level indicators, and instructional validation requirements. This approach enabled the generative AI system to produce educational materials corresponding to different cognitive complexity levels while preserving curriculum consistency and pedagogical coherence.

The large language model generated multiple categories of instructional materials, including theoretical questions, practical assignments, assessment tasks, conceptual explanations, and adaptive instructional guidance. Generated outputs were subsequently validated through semantic consistency checking, curriculum alignment verification, and pedagogical review procedures in order to reduce conceptual inconsistency and instructional inaccuracies.

The SPGF pipeline additionally integrated feedback-based adaptive analytics mechanisms capable of monitoring generation quality, competency alignment, and differentiated instructional balance. As illustrated in Figure 1, the proposed architecture established a structured interaction between educational standards, semantic curriculum structures, generative AI mechanisms, and pedagogical validation procedures.

The figure 2 illustrates the operational workflow of the proposed SPGF framework for differentiated educational content generation. The pipeline integrates curriculum extraction, CCN semantic parsing, JSON-based educational structuring, prompt engineering, NLP-driven generation, competency-level classification, pedagogical validation, adaptive analytics, and AI-generated homework construction within a unified curriculum-constrained educational architecture.

Figure 2. Step-by-Step NLP-Based Educational Generation Workflow

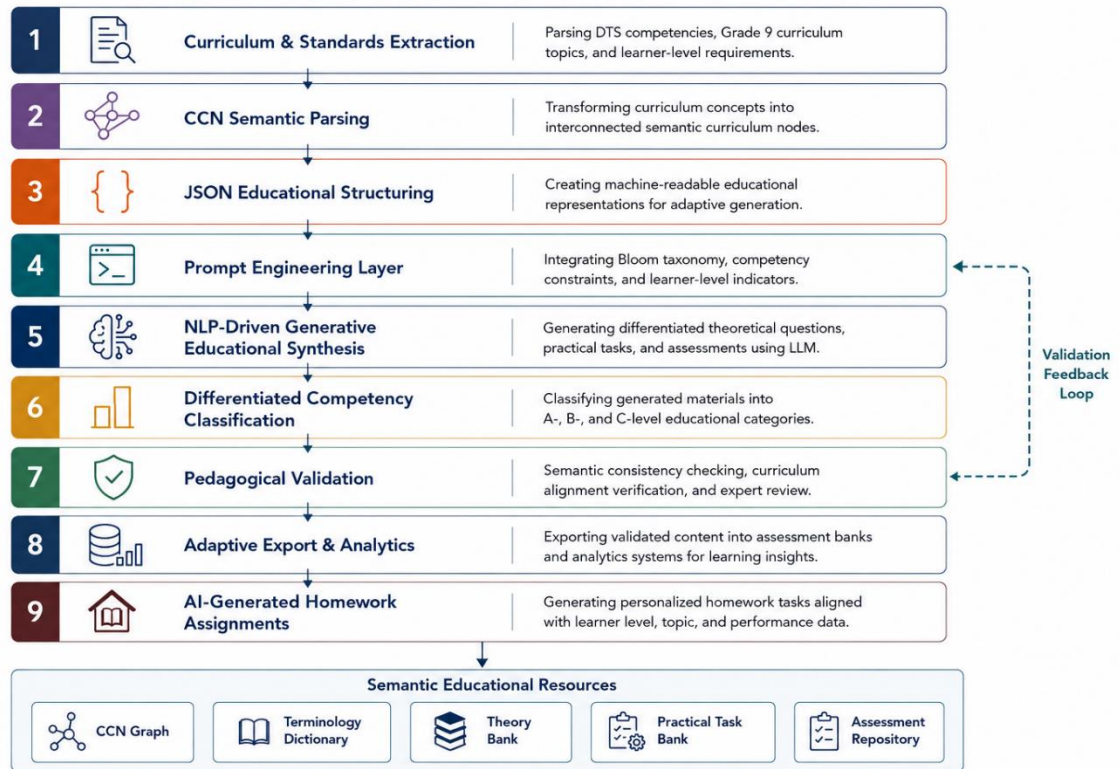


Figure 2. Step-by-Step NLP-Based Educational Generation Workflow.

Figure 2 demonstrates the sequential operational structure of the proposed SPGF framework. The workflow begins with curriculum and competency extraction procedures followed by semantic CCN parsing and machine-readable JSON educational structuring. Prompt engineering mechanisms integrate competency constraints, Bloom taxonomy levels, and differentiated learner indicators in order to guide NLP-based educational generation. The validation-feedback loop shown in the workflow enables recursive correction of semantic inconsistencies and pedagogical inaccuracies before deployment into adaptive assessment and homework generation systems. The proposed architecture therefore supports reliable differentiated instructional generation while preserving curriculum alignment and competency-oriented educational consistency

EXPERIMENTAL IMPLEMENTATION AND RESULTS

The experimental implementation of the proposed SPGF framework was conducted using Grade 9 Informatics curriculum materials aligned with Uzbekistan's state educational standards and Cambridge IGCSE instructional objectives. The curriculum content was transformed into structured JSON-based semantic educational representations consisting of Conceptual Curriculum Nodes (CCN), competency mappings, terminological dictionaries, theoretical knowledge structures, practical task repositories, and differentiated assessment components.

The implemented system integrated prompt engineering mechanisms, semantic curriculum parsing procedures, competency-oriented instructional constraints, Bloom taxonomy alignment rules, and Generative AI-based educational synthesis modules. Using this architecture, the SPGF framework automatically generated differentiated theoretical questions, practical assignments, adaptive assessments, and AI-generated homework tasks corresponding to A-, B-, and C-level learner categories. A total of 4,080 differentiated educational items were generated across 68 instructional topics. Figure 3 presents the classification reliability and cross-validation performance of the proposed SPGF framework for differentiated educational content generation.

Figure 3. Classification Reliability and Cross-Validation Results of the SPGF Framework

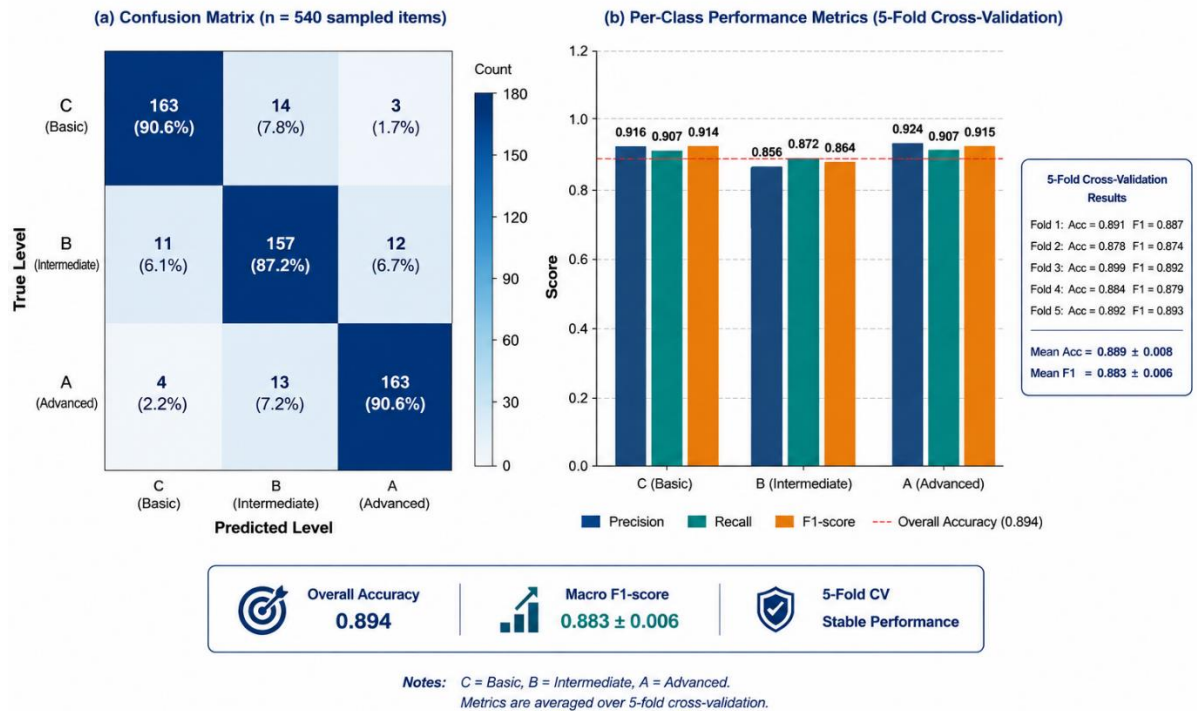


Figure 3. Classification Reliability and Cross-Validation Results of the SPGF Framework.

Figure 3 illustrates the classification reliability and cross-validation performance of the proposed SPGF framework for differentiated educational content generation. The confusion matrix demonstrates stable classification accuracy across C-, B-, and A-level learner categories, indicating strong correspondence between predicted and target competency levels. The per-class evaluation metrics further show high Precision, Recall, and F1-score values for all differentiated instructional categories, confirming the effectiveness of the proposed semantic educational representation and competency-oriented generation mechanisms. In addition, the 5-fold cross-validation results demonstrate stable experimental performance with a macro-average F1-score of 0.883 ± 0.006 and an overall classification accuracy of 0.894. These findings indicate that the integration of CCN semantic mapping, curriculum-constrained prompt engineering, and NLP-driven educational generation significantly improves the reliability, consistency, and pedagogical validity of AI-generated differentiated educational materials.

CONCLUSION

This study proposed the SPGF framework, a Generative AI-based adaptive methodology for differentiated educational content generation in secondary school Informatics education. The framework integrated competency-oriented educational standards, Conceptual Curriculum Node (CCN) semantic architectures, NLP-driven prompt engineering, and Generative AI technologies into a unified adaptive instructional system capable of automatically generating differentiated theoretical questions, practical assignments, adaptive assessments, and AI-generated homework activities for A-, B-, and C-level learner categories.

The experimental results demonstrated high reliability, semantic consistency, and pedagogical validity of the proposed methodology. The classification validation process achieved an overall accuracy of 0.894, while the 5-fold cross-validation procedure produced a macro-average F1-score of 0.883 ± 0.006 , indicating stable differentiated instructional classification performance across multiple competency levels. Furthermore, semantic alignment analysis

confirmed that 91.3% of generated educational materials satisfied curriculum-alignment requirements based on TF-IDF and cosine similarity evaluation procedures. The findings demonstrated that curriculum-constrained semantic architectures and CCN-based educational representations significantly improved the reliability and instructional consistency of AI-generated educational materials. Expert pedagogical evaluation additionally confirmed strong competency alignment, conceptual consistency, and methodological reliability within the generated instructional resources.

The proposed SPGF framework therefore demonstrates strong potential for implementation within Uzbekistan's competency-oriented educational system, particularly in Informatics education. The methodology can reduce teachers' manual workload while improving differentiated instructional personalization, competency-based assessment generation, and curriculum consistency. For once, artificial intelligence contributed something genuinely useful to education instead of merely generating confident paragraphs with the emotional depth of a malfunctioning calculator.

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