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SYSTEMATIC APPROACH TO CREATING EDUCATIONAL CONTENT USING ARTIFICIAL INTELLIGENCE IN MULTI-AGENT SYSTEMS

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Abstract—The article presents a systematic review of artificial intelligence methods for educational content generation in multi-agent systems. Modern approaches to the automatic generation of educational questions, lesson plans, and materials were analyzed using large language models. Four main groups of generation methods were distinguished: generation of educational questions and tasks using Bloom's taxonomy classification; generation of lesson plans using the step-by-step reasoning-prompting technique; generation with parametric control of complexity level; and pedagogically focused approaches that take into account the principles of constructivism in education. Proposed four types of classification of architectures of educational content generation systems: single-agent, hybrid, and multi-agent. Each type is characterized by the coordination approach, verification mechanisms, scalability, and content quality. It is shown that a significant proportion of systems positioned as multi-agent in fact belong to pipeline or hybrid architectures. Also, existing multi-agent content generation systems were analyzed, and the feasibility of using a multi-agent approach to build adaptive educational systems was demonstrated. A conceptual model of a multi-agent system for generating educational content is proposed, covering the ontological level, the content generation level, learner models, adaptation and personalization, agent coordination, quality assessment, and feedback. A reference architecture with five subsystems is proposed: planning, generation, evaluation, adaptation, and coordination. Key open issues are identified, critical risks of applying generative artificial intelligence in education are determined, and potential directions for further scientific research are outlined.

Keywords—Multi-agent systems, artificial intelligence, educational content, large language models, content generation, adaptive learning, intelligent educational systems.

I. INTRODUCTION

In recent years, the rapid development of generative artificial intelligence and large language models has significantly transformed approaches to creating digital educational resources. Automation of educational content development opens up new opportunities for personalizing learning, adapting educational materials to the individual needs of students, and increasing the efficiency of teachers. At the same time, the increasing complexity of educational scenarios requires a transition from the use of individual models to intelligent multi-agent systems capable of coordinating the processes of planning, generation, evaluation, and adaptation of educational materials.

The article provides a systematic review of modern methods for applying artificial intelligence to generate educational content in multi-agent

systems. Approaches to automatically creating educational questions, lesson plans, and educational materials based on large language models are analyzed. Four main groups of generation methods are distinguished: generation of educational questions and tasks with classification according to Bloom's taxonomy, generation of lesson plans using the step-by-step reasoning prompting technique, generation with parametric control of the level of complexity, and pedagogically oriented approaches that take into account the principles of constructivism. For each group, characteristic technical solutions, key evaluation metrics, and obtained results are defined.

A classification of architectures of educational content generation systems into four types is proposed: single-agent, pipeline, hybrid, and multi-agent. Each type is characterized by criteria of

coordination, verification mechanisms, scalability, and quality of generated content. It is shown that a significant part of systems that are positioned as multi-agent actually implement pipeline or hybrid architectures.

Based on the analysis, the feasibility of using a multi-agent approach for building adaptive educational systems is substantiated. A seven-level conceptual model of a multi-agent system for the formation of educational content has been developed, which covers the ontological level, levels of content generation, student model, adaptation and personalization, agent coordination, quality assessment and feedback organization. A reference architecture has been proposed, which includes subsystems of planning, generation, assessment, adaptation and coordination. Key open problems, risks of using generative artificial intelligence in education and promising areas of further scientific research have also been identified.

II. PROBLEM STATEMENT

Digital changes in education have significantly increased the need for high-quality, personalized educational content. Traditional approaches to creating educational materials do not provide the necessary level of adaptability and scalability, which makes the development of automated methods for generating content based on artificial intelligence (AI) very relevant. At the same time, the complexity of the educational process, which involves accounting for students' individual needs, pedagogical principles, and the specifics of the subject area, requires the use of multi-agent architectures that can distribute and coordinate the functions of generating, evaluating, and adapting content. Despite the significant progress in the development of individual methods of content generation and individual multi-agent architectures, there is no systematic generalization of the following areas: there is no classification of architectures of educational content generation systems, there is no comparative analysis of existing systems according to unified criteria, and conceptual models of multi-agent systems (MAS) for education are partial.

To achieve this goal, it is necessary to classify the architectures of educational content generation systems and conduct a comparative analysis of existing solutions. This comparative analysis is based on a defined set of metrics (criteria), including architectural flexibility (scalability), the level of agent autonomy, the types of educational content supported, as well as generation speed and adaptability to user needs.

Let there be a set of alternative architectural solutions for content generation systems, denoted as

$X = [x_1 \ x_2 \ \dots \ x_p]$. The analysis task involves evaluating each architecture based on a defined system of metrics E ,

$$f : X \times E \rightarrow V$$

where V represents the set of evaluation values. It is necessary to construct a mapping that identifies the advantages and limitations of existing solutions to provide a rationale for the proposed model.

III. ANALYSIS OF RECENT RESEARCH AND PUBLICATIONS

The issue of generating educational content using AI is being actively studied. Recent research [2] reviewed the use of generative AI in science education, revealing a 4.6-fold increase in publications in 2023–2024. In article [3], an analysis of research on artificial intelligence-generated educational content was conducted. Research [1] demonstrated the efficiency of classifying educational questions using Bloom's taxonomy, achieving a macro-F1 score of 0.70. In article [5], an automatic question-generation system was developed that achieved an F1 Score of 0.9523. In research [12] and [13], the multi-agent educational content generation systems GenMentor and EduPlanner are presented, which use exercise-generation mechanisms and an “evaluator-optimizer” architecture. The architectural principles for building multi-agent systems for digital learning are described in [20].

The following remain unresolved:

- the lack of a unified classification of architectures of educational content generation systems;
- the lack of comparative analysis of existing systems according to unified criteria;
- the fragmentation of conceptual models of MAS for education.

IV. FORMULATION OF THE OBJECTIVES OF THE ARTICLE

The main objective of the article is to systematize AI methods for generating educational content in MAS, develop a classification of architectures, and a conceptual model of the system.

To achieve this goal, it is necessary to classify the architectures of educational content generation systems, conduct a comparative analysis of existing solutions, and propose a conceptual MAS model for generating educational content.

V. MAIN RESEARCH MATERIAL

The formation of educational content is a multi-stage process that covers the full life cycle of

educational material: creation, adaptation, delivery, evaluation, feedback, updating, and archiving. Each stage can be automated by AI tools.

The generation of educational content is the process of automatically creating educational material (questions, tests, tasks, lesson plans, etc.) using AI methods, particularly Large Language Models (LLMs). An intelligent learning system is a software system that provides personalized learning by adapting the content and pace of instruction to the learner's needs. Modern systems integrate LLM for real-time content generation [14], [15].

A multi-agent system (MAS) consists of autonomous software agents that interact to achieve a common goal. In an educational context, MAS distributes the functions of content generation, evaluation, and adaptation among specialized agents [12], [13], [20]. A learner model is a formalized representation of a learner's knowledge and learning history for content personalization [17].

The literature analysis helped to identify four main groups of methods for generating educational content based on AI:

- 1) generation of educational questions and tasks;
- 2) generation of lesson plans and curricula;
- 3) generation with control over the level of complexity;
- 4) pedagogically oriented approaches.

Each group is characterized by specific approaches, types of input and output data, and quality assessment metrics. Below is provided a detailed analysis of each group of methods.

Automatic question generation is one of the most researched areas. Methods in this group can be divided into three subgroups according to the level of complexity of the request:

a) classification of existing questions by cognitive levels – in the study [1], the ability of LLM to classify educational questions by six levels of Bloom's taxonomy (from memorization to creation) was analyzed. With the use of vector representations, macro-F1 = 0.70 was achieved, which confirms the efficiency of LLM for automatic categorization of questions. In a further study, [7] an approach to question generation with cognitive level control;

b) generation of the questions based on educational texts - in work [5], a system based on pre-trained models with additional training for different subject areas was developed, F1-score = 0.9523 was achieved for the task of assessing the quality of generated questions;

c) generation of context-dependent questions = in research [8], a question generation system for

learning foreign languages using LLM and contextual prompts was proposed, demonstrating a statistically significant improvement in students' learning outcomes compared to traditional methods.

Generating lesson plans is a more complex task that requires consideration of pedagogical principles, learning objectives, and the sequence of material presentation. The research [9] proposes an LLM-based system for generating educational materials that employs a step-by-step reasoning method, enabling the model to sequentially decompose complex goals into discrete steps. Experts' reviews demonstrated high compliance of the generated plans according to educational standards.

The complexity control of generated content is critical for adaptive learning. The research [11] proposed a model for task generation with parametric complexity control, based on pre-trained LLMs and fine-tuning, where the complexity level is specified as a numeric parameter during generation. This approach allows precise adaptation of task complexity according to the student's level of training.

In study [6], a system "QuerIA" was developed to generate questions with automatic difficulty control, achieving over 80% accuracy in level determination. The system uses a subject-domain model to adjust question difficulty.

One more class of methods focuses on integrating pedagogical principles into the process of generating educational content. The study [4] examined the use of LLMs to generate formative tasks that incorporate constructivist principles of learning. The results showed that purposeful construction of prompts improves the quality of generated tasks.

In article [16], a generative pipeline for creating educational content was presented that integrates pedagogical templates and teachers' expert knowledge into the generation process.

An analysis of the data presented in Table I reveals two key trends. Firstly, there is a shift from simple content generation to generation that takes pedagogical requirements into account; methods are increasingly incorporating criteria such as complexity and pedagogical features. Secondly, the role of hybrid approaches is growing, with LLMs collaborating with human experts to produce higher-quality outcomes than fully automated methods.

Based on a review of the literature, a classification of educational content generation system architectures distinguished four types depending on the degree of component autonomy, coordination approach, and scalability. The

classification is based on an analysis of the structural features of the systems described in [10], [12] – [16] and generalizes them according to uniform criteria.

1) A single-agent architecture involves using a single LLM agent to perform all content generation functions, from analyzing learning objectives to creating the final version. The advantage is ease of implementation, but the limitations are the lack of verification mechanisms and the dependence of the quality of the results on a single model. A typical example is the direct use of ChatGPT or Claude to create educational materials.

2) Pipeline architecture organizes the generation process as a sequential processing chain, where each stage is performed by a separate module. The output of one stage serves as the input for the next. The advantage of this approach is improved quality

through step-by-step filtering; the limitations are the process's linearity and the lack of feedback between stages.

3) A hybrid architecture combines automated components with human involvement in the management process. The advantage is high-quality content thanks to human oversight; the limitations are dependence on experts and limited scalability.

4) Multi-agent architecture consists of a set of autonomous agents, each of which specializes in a specific function (generation, review, optimization, adaptation) and interacts with others via defined protocols. The advantages include high quality due to peer review among agents, scalability, and the ability to expand functionality. The limitations are the complexity of coordination and higher computational costs (Table II).

TABLE I. COMPARISON OF AI-BASED EDUCATIONAL CONTENT GENERATION METHODS

Generation method	Approach	Key Metric	Result
Question classification by Bloom	LLM + embeddings; 6 cognitive levels	macro-F1	0.57 → 0.70
Question generation based on educational material	Pre-trained LLM with fine-tuning	F1-score	0.9523
Context-dependent questions generation	LLM + contextual prompts	Learning results	Significant improvement
Lessons' plans generation	LLM + chain-of-thought	Expert review	Standards compliance
Lessons' plans generation	Hybrid human-AI	Comparison with ChatGPT	Significant improvement
Parametric difficulty control	Pre-trained LLMs; numeric parameter	Accuracy of difficulty level	Controlled generation
Adaptive complexity control	QuerIA; domain-specific model	Complexity level accuracy	> 80%
Pedagogically oriented generation	LLM + prompt engineering	Pedagogical quality	Significant improvement

TABLE II. A COMPARATIVE ANALYSIS OF ARCHITECTURAL APPROACHES TO EDUCATIONAL CONTENT DEVELOPMENT SYSTEMS

Criteria	Single-agent	Pipeline	Hybrid	Multi-agent
Number of components	1 LLM-agent	2–3 sequential modules	2–4 (LLM + human)	3+ autonomous agent
Coordination pattern	None	Linear	Human in the management	Autonomous interaction
Verification mechanism	None	Step-by-step filtering	Validation by expert	Mutual verification of agents
Scalability	Low	Medium	Limited (depends on the expert)	High
Adaptability	Depends on prompt	Limited (fixed chain)	High (manual)	High (automatic)
Content quality	Unstable	Improved by filtering	High (human control)	High (iterative improvement)

It is important to note that a significant portion of the systems described by the authors as “multi-agent” are in fact pipeline or hybrid architectures,

since the agents in these systems lack true autonomy and interact only linearly. The criteria for classification as a multi-agent architecture include

the presence of autonomous agents with defined roles, capable of mutual verification, iterative improvement, and flexible task distribution.

A comparative analysis of the modern educational content generation systems shows that multi-agent architectures deliver higher-quality results due to the distribution of functions among specialized agents and peer-review mechanisms. This demonstrates the feasibility of using a multi-agent approach to build adaptive and scalable educational content generation systems.

An analysis of multi-agent educational systems highlights several typical approaches to agent coordination. The “generator-critic” approach involves a content-generating agent and a reviewer agent that evaluates and filters the generated material. The “evaluator-optimizer” approach uses an iterative cycle in which the evaluator agent identifies weaknesses in the material, and the optimizer agent eliminates them. Agent coordination can be centralized (a single dispatcher agent distributes tasks) or decentralized (agents self-organize via interaction protocols).

Based on the analysis of the literature and existing systems, a seven-level conceptual model of a multi-agent system for educational content generation is proposed. The model integrates the approaches described in [12] – [14], [20] and synthesizes the architectural solutions into a unified approach.

1) The ontological level defines the structure of the domain through knowledge graphs, including relationships, prerequisites, and levels of cognitive complexity [18], [19].

2) The content generation level includes the processes of automatically creating learning materials using an LLM, taking into account ontological constraints and pedagogical requirements.

3) The learner model level supports the creation and updating of individual learner profiles, including knowledge level, learning style, and learning history.

4) The adaptation and personalization level ensures that material is customized according to the student’s profile, including the selection of difficulty, presentation format, and sequence of material.

5) The agent coordination level provides protocols for interaction between agents, role distribution, and conflict resolution mechanisms.

6) The assessment and quality level integrates methods of automated and expert evaluation of the quality of generated content, including metrics and psychometric indicators.

7) The feedback and adaptation level closes the loop, helping to improve content based on

assessment results and analysis of student interactions with the material.

Based on an analysis of existing systems, a reference MAS architecture comprising five subsystems is proposed:

1) planning – decomposition of learning objectives;

2) generation – creation of various types of content;

3) assessment – quality control;

4) adaptation – tailoring content to the learner’s model;

5) coordination – managing agent interaction.

VI. CONCLUSIONS

During this study, current methods for generating educational content using artificial intelligence were systematized, specifically, approaches to the automated generation of questions, lesson plans, and educational materials with controlled levels of difficulty. It has been established that the use of LLMs enables high levels of automation in creating educational content and opens opportunities for adaptive and personalized learning.

A classification of educational content generation system architectures has been formed, identifying single-agent, pipeline, hybrid, and multi-agent approaches. It has been determined that multi-agent architectures offer advantages in terms of scalability, adaptability, and content quality due to coordination and mutual verification mechanisms between agents.

A seven-level conceptual MAS model for educational content development is proposed, covering the entire content lifecycle. The proposed model synthesizes current approaches to the design of intelligent educational systems and can serve as a foundation for further development.

The study identified several outstanding issues and limitations in the field of educational content generation in MAS. The main ones include the lack of a consistent taxonomy of agent roles, a shortage of comparative studies on mechanisms for shared memory and agent coordination, the absence of a unified set of metrics for evaluating content quality, and insufficient research on “human-in-control” interaction models. A separate issue is the lack of long-term studies to assess the impact of AI-generated content on learning outcomes.

Also, current risks associated with the use of generative artificial intelligence in education include the generation of factually incorrect information, pedagogically inaccurate content for the target audience, and excessive dependence on specific LLM models.

Prospects for further research include the development of a standardized taxonomy of agent roles, the creation of unified tools and metrics for comparative evaluation of systems, the study of teacher-involved control models, the integration of knowledge graphs for managing the lifecycle of educational content, and the conduct of long-term experimental studies on the impact of AI-generated content on learning effectiveness.

The scientific novelty of the obtained results lies in the development – for the first time – of a conceptual model of a multi-agent system for generating educational content; unlike existing solutions, this model is based on the integration of hybrid artificial intelligence methods and the dynamic interaction of specialized agents, enabling the automation of test material creation with a higher level of adaptation to the learner's needs.

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Ю. В. Мельник, С. І. Отрох, А. О. Пасічніук, В. О. Кузьмініх. Систематизований підхід створення навчального контенту штучним інтелектом в мультиагентних системах

У статті представлено систематичний огляд методів штучного інтелекту для генерації навчального контенту в мультиагентних системах. Проаналізовано сучасні підходи до автоматичної генерації навчальних запитань, планів уроків і матеріалів на основі великих мовних моделей. Виділено чотири основні групи методів генерації: генерація навчальних запитань та завдань із класифікацією за таксономією Блума, генерація планів уроків із використанням техніки промптингу покрокового міркування, генерація із параметричним контролем рівня складності та педагогічно орієнтовані підходи з урахуванням принципів конструктивізму в освіті. Для кожної групи методів виокремлено технічні підходи, ключові метрики та отримані результати. Запропоновано класифікацію архітектур систем формування навчального контенту за чотирма типами: одноагентна, конвеєрна, гібридна та мультиагентна. Кожен тип охарактеризовано за критеріями підходу координації, механізму верифікації, масштабованості та якості контенту. Показано, що значна частина систем, які позиціонуються як мультиагентні, фактично належить до конвеєрних або гібридних архітектур. Проаналізовано наявні мультиагентні системи генерації контенту та обґрунтовано доцільність використання мультиагентного підходу для побудови адаптивних освітніх систем. Розроблено семирівневу концептуальну модель мультиагентної системи формування навчального контенту, що охоплює онтологічний рівень, рівень генерації контенту, моделі учня, адаптації та персоналізації, координації агентів, оцінювання якості та зворотного зв'язку. Запропоновано референтну архітектуру із п'ятьма підсистемами: планування, генерації, оцінювання, адаптації та координації. Ідентифіковано ключові відкриті проблеми, визначено критичні ризики застосування генеративного штучного інтелекту в освіті та окреслено перспективні напрями подальших наукових досліджень.

Ключові слова: мультиагентні системи, штучний інтелект, навчальний контент, великі мовні моделі, генерація контенту, адаптивне навчання, інтелектуальні навчальні системи.

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Напрямок наукової діяльності: ергатичні системи, інтелектуальні системи управління.

Кількість публікацій: 76.

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