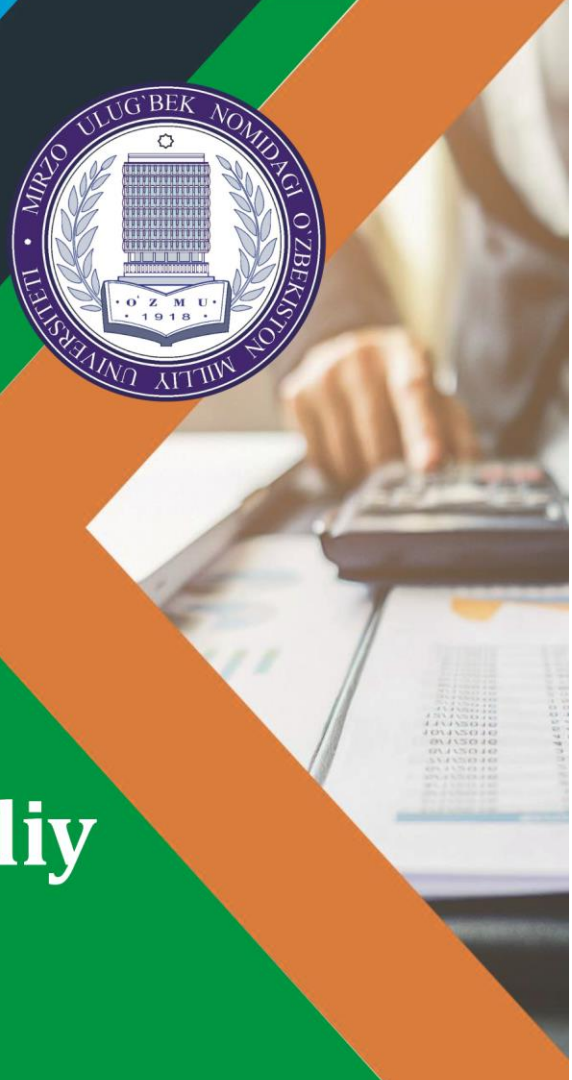

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RETRIEVAL-AUGMENTED GENERATIVE AI FOR SMART LEARNING CONTENT

AQLLI TA’LIM KONTENTI UCHUN MA’LUMOTLARNI QIDIRIB-KENGAYTIRILGAN GENERATIV SUN’IY INTELLEKT

ПОИСКОВО-ДОПОЛНЕННЫЙ ГЕНЕРАТИВНЫЙ ИИ ДЛЯ ИНТЕЛЛЕКТУАЛЬНОГО УЧЕБНОГО КОНТЕНТА

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Annotation

This article analyses the economic and pedagogical efficiency of retrieval-augmented generation (RAG) for the production of smart learning content. Drawing on industry analyses by MarketsandMarkets, Precedence Research, and NMSC, and on peer-reviewed studies from 2024–2026, it shows that the global RAG market is projected to grow from USD 1.94 billion in 2025 to USD 9.86 billion in 2030 (CAGR 38.4%), and that systems such as MEDRAG and Finetune-RAG improve answer accuracy by 18–21% and reduce hallucinations by 15–19% relative to baseline large language models.

Keywords: RAG, generative AI, learning content, large language models, vector databases, digital education, hallucination reduction, intelligent tutoring systems.

Ushbu maqolada aqlli ta’lim kontentini yaratish uchun ma’lumotlarni qidirib-kengaytirilgan generativ sun’iy intellekt (RAG) texnologiyasining iqtisodiy va pedagogik samaradorligi tahlil qilinadi. MarketsandMarkets, Precedence Research va NMSC analitik hisobotlari hamda 2024–2026-yillardagi retsenziyalangan tadqiqotlarga tayangan holda RAG bozorining 2025-yildagi 1,94 mlrd AQSh dollaridan 2030-yilda 9,86 mlrd AQSh dollarigacha (CAGR 38,4%) o‘sishi, MEDRAG va

Finetune-RAG kabi tizimlarda javoblar aniqligi 18–21% gacha oshishi va galyutsinatsiyalar darajasi 15–19% gacha kamayishi ko‘rsatib berilgan.

Kalit so‘zlar: RAG, generativ sun’iy intellekt, ta’lim kontenti, katta til modellari, vektor ma’lumotlar bazalari, raqamli ta’lim, galyutsinatsiyalarni kamaytirish, intellektual o‘qitish tizimlari.

В статье анализируется экономическая и педагогическая эффективность технологии поисково-дополненной генерации (RAG) при создании интеллектуального учебного контента. На основе отчётов MarketsandMarkets, Precedence Research и NMSC, а также рецензируемых исследований 2024–2026 годов показано, что мировой рынок RAG вырастет с 1,94 млрд долл. США в 2025 году до 9,86 млрд долл. США в 2030 году (CAGR 38,4%), а такие системы, как MEDRAG и Finetune-RAG, повышают точность ответов на 18–21% и снижают уровень галлюцинаций на 15–19% по сравнению с базовыми моделями.

Ключевые слова: RAG, генеративный ИИ, образовательный контент, большие языковые модели, векторные базы данных, цифровое образование, снижение галлюцинаций, интеллектуальные обучающие системы.

The expansion of generative artificial intelligence (AI) into the educational sector since the public release of ChatGPT in late 2022 has been accompanied by a parallel concern: large language models (LLMs) are powerful but fluent fabricators, prone to producing plausible-sounding yet factually wrong content. In the classroom, where epistemic accuracy is non-negotiable, this risk is decisive. Retrieval-augmented generation (RAG) — a hybrid architecture in which a language model is paired with an external knowledge retriever that supplies vetted passages at generation time — has emerged as the dominant industrial response to this problem and, by extension, as a foundational technology for smart, personalised learning content. This paper reviews the algorithmic principles of RAG, the empirical evidence on its effectiveness, the size and trajectory of its commercial market, and the policy implications of deploying RAG in school, university, and corporate learning environments [1; 2].

At its core, a RAG pipeline consists of three components: an indexed knowledge base (most commonly stored in a vector database such as Pinecone, Weaviate, or Milvus), a retriever that returns the top-k passages most relevant to a learner’s query, and a generator (an LLM) that produces the final natural-language response conditioned on those passages. The integration of retrieval into the generation step provides two pedagogically critical guarantees that pure LLMs cannot offer. First, the answer is grounded in a controllable, auditable corpus — a textbook, a curated course library, an institutional knowledge base — rather than in the model’s opaque parametric memory. Second, the corpus can be updated continuously without retraining the model, which means that learning content can incorporate the latest scholarship, regulatory updates, or institution-specific materials at low marginal cost [3].

Recent technical contributions have refined this baseline architecture along several axes. Corrective RAG (CRAG) introduces adaptive retrieval evaluation that re-queries the knowledge base when the initial retrieval is judged insufficient. Adaptive-RAG dynamically scales the retrieval depth to match query complexity. Self-RAG inserts self-reflection tokens into the generator to enable on-the-fly verification of supporting evidence. Knowledge-graph extensions such as GraphRAG and KRAGEN reformulate retrieval as multi-hop reasoning over an explicit ontology, which is particularly relevant for structured subjects such as mathematics, anatomy, or legal doctrine [4]. Across these variants the design objective is the same: align the generated text more tightly with retrievable, citable evidence.

The empirical case for RAG in education and adjacent knowledge-work domains has strengthened markedly during 2024–2025. The MIRAGE benchmark, comprising 7,663 medical questions, demonstrated that the MEDRAG toolkit raises the accuracy of six different LLMs by up to 18% over chain-of-thought prompting alone, lifting GPT-3.5 and Mixtral to a GPT-4-level on biomedical question answering [5]. The Finetune-RAG approach, evaluated on a deliberately imperfect retrieval benchmark, reported a 21.2% improvement in factual accuracy over a strong base

model [6]. A 2024 study of RAG in healthcare workflows recorded a 15% reduction in diagnostic errors relative to pure-LLM baselines [7], and hybrid retrieval over legal documents produced a 15% improvement in retrieval precision in OpenAI Labs’ 2024 evaluations [8]. A 2025 systematic survey of RAG chatbots for education by the journal Applied Sciences identified 47 primary studies (37 published in 2024 alone) and concluded that RAG’overcomes the main barrier for the adoption of LLM-based chatbots in education: hallucinations’ [9].

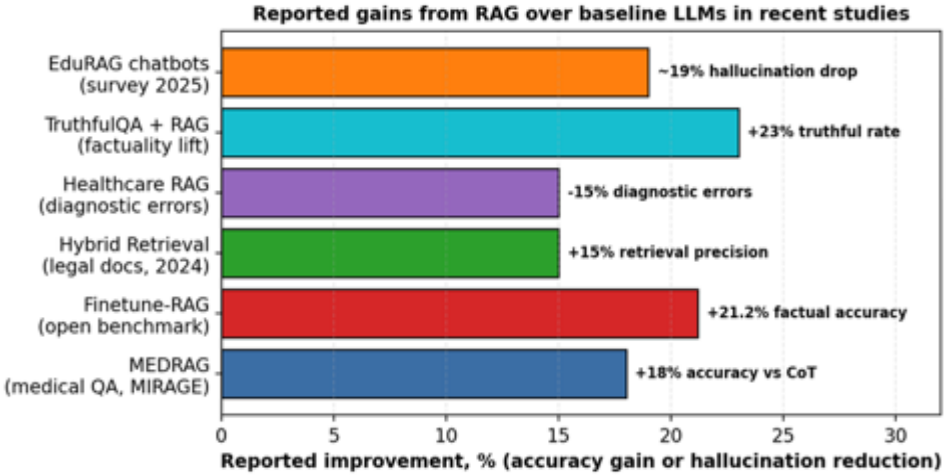

Fig 1. Reported gains from RAG over baseline LLMs in recent studies, 2024–2025.

The commercial dynamics reflect the same trajectory. As Figure 2 shows, three independent industry analysts converge on a strongly positive growth outlook for the global RAG market. MarketsandMarkets estimates the market at USD 1.94 billion in 2025 and projects USD 9.86 billion by 2030 at a CAGR of 38.4% [10]. Precedence Research reports USD 1.85 billion in 2025 and a far steeper trajectory of USD 67.42 billion by 2034 at a CAGR of 49.12% [11]. Next Move Strategy Consulting (NMSC) places the 2025 baseline at USD 2.33 billion and forecasts USD 81.51 billion by 2035 at a CAGR of 42.7% [12]. Despite the variation in scope and time horizon, all three forecasts agree on two structural facts: North America currently dominates with the largest share, and Asia-Pacific is the fastest-growing region. For an emerging economy such as Uzbekistan, in which the Presidential Resolution PP-358 of October 2024 has identified education as a priority for AI deployment, the implication is that the cost of entry into RAG-based educational platforms is falling rapidly even as the technology matures.

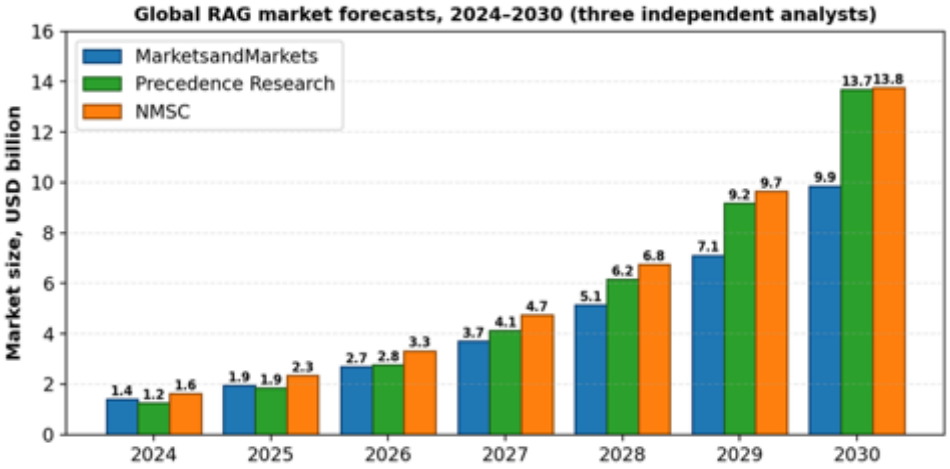

Fig 2. Global RAG market forecasts, 2024–2030 (three independent analysts).

Table 1 consolidates the key statistical evidence on RAG and its application to learning content, together with the principal sources from which the figures are drawn. The pattern across the rows is consistent: every well-instrumented RAG deployment reports double-digit accuracy gains or

hallucination reductions over baseline LLMs, while market forecasts uniformly project compound annual growth rates well above 35%.

Table 1.

RAG market dynamics and reported performance gains in education and adjacent domains.

Indicator	Source	Value
Global RAG market size, 2025	MarketsandMarkets [10]	USD 1.94 bn
Global RAG market size projected, 2030	MarketsandMarkets [10]	USD 9.86 bn
RAG market CAGR, 2025–2030	MarketsandMarkets [10]	38.4%
RAG market projected, 2034	Precedence Research [11]	USD 67.42 bn
RAG market projected, 2035	Next Move Strategy Consulting [12]	USD 81.51 bn
MEDRAG accuracy gain over chain-of-thought (MIRAGE)	Xiong et al., 2024 [5]	+18%
Finetune-RAG factual accuracy gain over base	Lee et al., 2025 [6]	+21.2%
Hallucination drop in education-focused RAG chatbots	Applied Sciences survey 2025 [9]	~19%
Diagnostic-error reduction in healthcare RAG	Chitika RAG Guide 2025 [7]	15%
Retrieval-precision gain, hybrid retrieval (legal docs)	OpenAI Labs 2024 [8]	+15%
Education-focused RAG studies in 2024 (survey)	Applied Sciences 2025 [9]	37 papers

Three implications follow for the design and procurement of smart learning content. First, the algorithmic gains achievable through RAG are not marginal but transformational: a 15–21% lift in accuracy, when applied to assessments or to lesson generation, translates directly into measurable learning gains and into a reduction in faculty time spent correcting AI-generated errors. Second, the architectural pattern is now sufficiently standardised that small institutions and emerging-market universities can deploy production-grade RAG without proprietary research budgets: cloud hyperscalers (Azure OpenAI, AWS Bedrock, Google Vertex) and open-source toolkits (LangChain, LlamaIndex, Haystack) supply the entire stack as a managed service. Third, the educational value of RAG depends critically on the quality of the underlying corpus. A RAG system anchored in vetted textbooks and peer-reviewed sources produces reliable learning content; the same architecture grounded in an unvetted web crawl reproduces the very hallucinations it was meant to fix [9; 13].

Several concrete implementation pathways follow from this roadmap for Uzbekistan’s educational system. A pilot retrieval corpus could be assembled from the digitised national curriculum, peer-reviewed monographs of leading domestic researchers, and the open-access teaching materials of the country’s flagship universities — Tashkent State University of Economics, Samarkand State University, and Fergana State University, among others — indexed in a vector database accessible through a centralised inference gateway. Such a corpus would simultaneously address the equity-of-access concern, by reducing dependence on English-language commercial RAG services, and the factuality concern, by anchoring generation in source materials whose authorship and editorial provenance are known.

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SANOAT KORXONALARINI BARQAROR RIVOJLANTIRISH MEXANIZMLARINI TAKOMILLASHTIRISH: ILMIY-NAZARIY VA AMALIY ASOSLAR

СОВЕРШЕНСТВОВАНИЕ МЕХАНИЗМОВ УСТОЙЧИВОГО РАЗВИТИЯ ПРОМЫШЛЕННЫХ ПРЕДПРИЯТИЙ: НАУЧНО-ТЕОРЕТИЧЕСКИЕ И ПРАКТИЧЕСКИЕ ОСНОВЫ

IMPROVING MECHANISMS FOR SUSTAINABLE DEVELOPMENT OF INDUSTRIAL ENTERPRISES: SCIENTIFIC-THEORETICAL AND PRACTICAL FOUNDATIONS

Ergashev Sarvar Alisher o‘gli
Islom Karimov nomidagi Toshkent davlat texnika universiteti
“Sanoat iqtisodiyoti va menejmenti” kafedrasi tayanch doktoranti.

Annotatsiya

Mazkur ilmiy maqolada sanoat korxonalarini barqaror rivojlantirish mexanizmlarini takomillashtirishning nazariy va amaliy jihatlari chuqur tahlil qilinadi. Tadqiqot jarayonida sanoat korxonalarida resurslardan samarali foydalanish, innovatsion rivojlanish, ekologik boshqaruv va raqamli transformatsiya masalalari kompleks yondashuv asosida o‘rganildi. Muallif tomonidan sanoat korxonalarining barqaror rivojlanishini ta’minlashga qaratilgan integratsiyalashgan model ishlab chiqilgan va uning samaradorligi asoslab berilgan.

Kalit so‘zlar: barqaror rivojlanish, sanoat korxonalari, innovatsion iqtisodiyot, raqamlashtirish, ekologik boshqaruv, resurs samaradorligi, sanoat siyosati.

В данной научной статье исследуются научно-теоретические и практические основы совершенствования механизмов устойчивого развития промышленных предприятий. В ходе исследования на основе комплексного подхода были проанализированы вопросы эффективного использования ресурсов на промышленных предприятиях, развития инновационной деятельности, внедрения систем экологического управления и процессов цифровой трансформации. Наряду с повышением экономической эффективности предприятий были изучены факторы обеспечения экологической и социальной устойчивости. Автором разработана интегрированная модель управления, направленная на обеспечение устойчивого развития промышленных предприятий, а также обоснована её практическая эффективность. Результаты исследования имеют важное значение для повышения