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COLD-START IN EDUCATIONAL RECOMMENDER SYSTEMS: CLASSICAL AND LLM-ERA STRATEGIES

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Abstract. Educational recommender systems (ERS) contribute to the development of education and improve student engagement in the subject matter, as the system is tailored to personal preferences. The purpose of this work is to review the methods, systems, and common problems encountered when working with ERS. In particular, the Cold-Start problems in launching new items. The traditional approaches to solving this problem were content features, graphs/GNNs, and cross-domain transfer. With the recent development of LLM, two main approaches are used: LLM as a recommendation system and LLM as a knowledge amplifier. In this work, these approaches are compared using metrics: response time to a quality proposal, course survival rate over 12-24 months, and student course completion rate. Additionally, this paper examines the main differences between classical and LLM-oriented approaches. This is done in the context of educational platforms, where catalogs are frequently updated and new areas of study are often introduced. Particular attention is paid to three cold start scenarios: a new learner with no interaction history, a new course with a minimum number of clicks and reviews, and a new region. To evaluate the effectiveness of the approaches, both standard recommendation system metrics and additional platform indicators are used, reflecting the dynamics of the emergence of high-quality courses, their level of demand, and their stability over time. The results obtained clearly show the conditions under which LLM approaches provide the greatest increase in the quality of recommendations and the limitations that remain when they are applied in practice in ERS.

Keywords: Educational Recommender Systems (ERS), Cold-Start Problem, Large Language Models (LLM), Retrieval-Augmented Generation (RAG), Hybrid Recommendation Models, Evaluation Metrics

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БІЛІМ БЕРУ САЛАСЫНДАҒЫ ҰСЫНЫМДЫҚ ЖҮЙЕЛЕРІНДЕГІ «COLD-START» МӘСЕЛЕСІ: КЛАССИКАЛЫҚ ӘДІСТЕР ЖӘНЕ LLM ДӘУІРІНІҢ СТРАТЕГИЯЛАРЫ

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Аннотация: Білім беру саласындағы ұсынымдық жүйелер (ERS) білім берудің дамуына ықпал етеді және жүйе пайдаланушының жеке қалауларына бейімделгендіктен, студенттердің пәнге қызығушылығын арттырады. Бұл жұмыстың мақсаты – ERS-пен жұмыс істеу барысында қолданылатын әдістерді, жүйелерді және жиі кездесетін мәселелерді шолу. Атап айтқанда, жаңа элементтерді іске қосу кезіндегі «cold start» мәселесі қарастырылады. Бұл мәселені шешудің дәстүрлі тәсілдеріне контенттік сипаттамалар, графтар/графтық нейрондық желілер (GNN) және домендер арасындағы трансфер жатады. Соңғы уақытта үлкен тілдік модельдердің (LLM) дамуына байланысты екі негізгі тәсіл қолданылады: LLM-ді ұсынымдық жүйе ретінде пайдалану және LLM-ді білімді күшейтуші құрал ретінде қолдану. Бұл жұмыста аталған тәсілдер келесі метрикалар бойынша салыстырылады: сапалы ұсынысқа жауап беру уақыты, 12–24 ай аралығындағы курстың өміршеңдік деңгейі және студенттердің курсты аяқтау көрсеткіші. Сонымен қатар, мақалада классикалық және LLM-бағытталған тәсілдердің негізгі айырмашылықтары талданады. Зерттеу білім беру платформалары контекстінде жүргізілді, мұнда курстар каталогы жиі жаңартылып отырады және жаңа оқу бағыттары үнемі енгізіледі. Ерекше назар «cold start» мәселесінің үш сценарийіне аударылады: өзара әрекеттесу тарихы жоқ жаңа білім алушы, қаралымдары мен пікірлері аз жаңа курс және жаңа аймақ. Тәсілдердің тиімділігін бағалау үшін ұсынымдық жүйелердің стандартты метрикаларымен қатар, платформаның қосымша көрсеткіштері де қолданылады. Бұл көрсеткіштер сапалы курстардың пайда болу динамикасын, олардың сұраныс деңгейін және уақыт өте келе тұрақтылығын сипаттайды. Алынған нәтижелер LLM тәсілдері қандай жағдайларда ұсыным сапасын айтарлықтай арттыратынын және оларды білім беру ұсынымдық жүйелерінде практикалық қолдану барысында сақталатын шектеулерді айқын көрсетеді.

Түйін сөздер: Білім беруге арналған ұсыныс жүйелері (ERS), салқын басталу мәселесі, үлкен тілдік модельдер (LLM), ақпаратты іздеу арқылы толықтырылған генерация (RAG), гибридті ұсыныс модельдері, бағалау көрсеткіштері

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ХОЛОДНЫЙ ЗАПУСК В СИСТЕМАХ РЕКОМЕНДАЦИЙ В ОБЛАСТИ ОБРАЗОВАНИЯ: КЛАССИЧЕСКИЕ СРЕДСТВА И СТРАТЕГИИ LLM ЭПОХИ

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Аннотация: Системы рекомендаций в образовании (ERS) играют важную роль в персонализации обучения и повышении вовлечённости студентов за счёт адаптации контента к индивидуальным предпочтениям пользователей. Целью данной работы является анализ существующих методов, архитектур и ключевых проблем, возникающих при разработке и эксплуатации образовательных рекомендательных систем. Особое внимание уделяется проблеме «холодного старта», возникающей при добавлении новых пользователей, курсов, каталогов или выходе на новые рынки. Традиционные подходы к решению данной проблемы включают контентно-ориентированные методы, графовые модели (включая GNN) и междоменный перенос знаний. В условиях стремительного развития больших языковых моделей (LLM) формируются новые подходы, среди которых выделяются два ключевых направления: использование LLM как самостоятельной рекомендательной системы и применение LLM в качестве усилителя знаний (knowledge augmentation). В работе проводится сравнительный анализ указанных подходов на основе ряда метрик, включая время отклика на формирование рекомендаций, коэффициент удержания курсов в течение 12–24 месяцев и уровень завершения курсов пользователями. Особое внимание уделяется трём сценариям «холодного старта»: новый пользователь без истории взаимодействия; новый курс с ограниченным числом взаимодействий (клики, отзывы); новый регион или витрина с отличающимися лингвистическими и культурными характеристиками. Для оценки эффективности используются как стандартные метрики рекомендательных систем, так и дополнительные платформенные показатели, отражающие динамику появления качественного контента, уровень его востребованности и устойчивость во времени. Полученные результаты демонстрируют условия, при которых подходы на основе LLM обеспечивают наибольшее повышение качества рекомендаций, а также выявляют ограничения их практического применения в образовательных системах.

Ключевые слова: образовательные системы рекомендаций (ERS), проблема «холодного старта», большие языковые модели (LLM), генерация

с расширенным поиском (RAG), гибридные модели рекомендаций, метрики оценки

Introduction. Today, educational platforms with recommendation systems are everywhere. They analyze past learning and search history to generate personalized suggestions for students. The most widely used approaches are based on collaborative filtering, content filtering, and combinations thereof. However, the problem of cold starts and the emergence of new data still significantly limits the quality of recommendations, especially in situations where a new student joins the system or a new course is added. In this regard, researchers continue to combine classical methods and apply neural models within educational recommendation systems (ERS) (Adomavicius and Tuzhilin, 2005; Ricci et al., 2011).

Despite significant progress in this area, existing studies tend to focus either on individual algorithmic solutions or do not fully take into account modern AI-oriented and platform-based approaches. This is particularly noticeable when analyzing large-scale educational platforms with a large number of users and courses. Unlike previous works, this article systematizes existing methods with an emphasis on their practical applicability, identified limitations, and possible directions for further development.

Literature review. Why this issue is particularly important now. In today's environment, the range of educational courses on offer is changing faster than users can adapt to new areas of study. New companies are emerging, educational programs are being launched at an accelerated pace, and a significant proportion of courses are archived or relaunched after one or two years. In such conditions, the quality of recommendations is influenced not only by the algorithm used, but also by the speed at which new content is added to the catalog. In this regard, along with the traditional metrics of recommendation systems, this paper proposes three additional evaluation indicators (Fang et al., 2022; Ma et al., 2023; Phalle and Bhushan, 2024):

- The delay between the peak of public interest in a new profession and the emergence of high-quality courses on the subject.
- We take the completion rate as the main parameter for the quality indicator for courses six or twelve months after release.
- Survivability, i.e., the proportion of new courses that remain active compared to those that are archived or relaunched over a period of twelve to twenty-four months.

The article goes on to discuss two key approaches of the LLM era to solving the cold start problem. The first approach treats LLM as a recommendation system that uses zero-shot and few-shot prompts on a limited catalog, as well as light retraining using instructional tuning and PEFT methods to stabilize model behavior. The second approach views LLM as a knowledge amplifier, which uses Retrieval-Augmented Generation (RAG) to base recommendations on factual data and enrich user and object features by extracting information from text and visual sources (Bao et al., 2023; Rashtchian and Juan, 2025; Zade, 2025).

Contribution. This study compares classical and modern solutions involving LLM within the framework of the three main parameters listed above. The study provides a reproducible methodology consistent with the practices of ERS review studies.

2.Materials and Methods

2.1 Research Objectives and Questions

Research objective. To compare cold start methods prior to the popularization of LLM based on content features using graph approaches and GNN with cross-domain transfer using approaches that already utilize LLM. The study considers and compares two approaches. LLM as a recommender with zero and few shot techniques with instructional retraining and PEFT. LLM as a knowledge amplifier using RAG and feature enrichment. The comparison is carried out in three cold start situations. CS User is a new learner with no history of recommendation systems. CS Item is a new course with a small number of clicks and reviews. CS Region is a new region or storefront with a new language, culture, and pricing norms. (Schein et al., 2002; Zhu et al., 2020; Geng et al., 2022).

Research questions.

1. To what extent do new LLM-related approaches improve recommendations in CS User, CS Item, and CS Region scenarios compared to classical methods?

2. Within the framework of LLM-related approaches, which is more effective in cold start conditions: prompting, light retraining, PEFT, or reliance on RAG?

2.2 Review Design and Source Gathering

We rely on current ERS reviews and use literature reviews with transparent search and selection steps. We follow a proven sequence. Selection of suitable databases. Setting Boolean queries. Inclusion and exclusion criteria. Thematic classification into six blocks. Background and key concepts. Approaches. Challenges. Applications. Evaluation. Future directions ERS databases. Google Scholar ScienceDirect IEEE Xplore ACM DL Springer. For the latest results, we use arXiv. (Adomavicius and Tuzhilin, 2005; Ricci et al., 2011; Butmeh et al., 2024; Fang et al., 2022).

Search formulas. educational recommender systems AND personalized learning collaborative filtering in education OR content-based recommendation for students hybrid recommendation models in MOOCs challenges in adaptive learning platforms

Inclusion criteria. Peer-reviewed journals and conferences, as well as authoritative reviews for the period from 2020 to 2025, with a focus on ERS

Exclusion criteria. Materials outside ERS, duplicate works.

Classification. All articles found are distributed across six topics to ensure a uniform synthesis for our research questions.

Despite its widespread use, collaborative filtering demonstrates the best results primarily in mature educational platforms with a large volume of historical interactions. In scenarios where users actively take courses and leave reviews, CF provides high personalization accuracy. However, in dynamic educational environments characterized by the frequent appearance of new users and courses, CF's dependence on accumulated interactions becomes a systemic limitation. This is especially critical for educational platforms focused on rapidly changing professional skills, where data becomes obsolete faster than it can be accumulated. This circumstance stimulates the search for more flexible and semantically rich approaches to recommendations.

2.3 Technical Baselines and LLM-Era Conditions

Classic basic methods. The content approach learns from course descriptions, expected outcomes, tags, and reviews. Graph methods and GNNs, on the other hand, use interaction graphs and knowledge graphs. Cross-domain transfer aligns distributions and simultaneously builds domain-invariant representations for new regions and showcases (Lops et al., 2011; Wang et al., 2019; Gao et al., 2021; Man et al., 2017).

LLM as a recommender. Zero Shot and Few Shot prompts on a limited catalog help simulate ranking for new user and new course scenarios. Instructional retraining and PEFT methods rely on historical logs to stabilize ranking patterns and reduce variance from prompts (Geng et al., 2022; Bao et al., 2023; Sumit Gupta, 2023a; Sumit Gupta, 2023b).

LLM as a knowledge amplifier. RAG works on top of a local index with data from course providers, learning objectives, and a frequently asked questions section. This grounds object profiles and reduces hallucinations. Feature enrichment extracts signals about skill level and learning outcomes from the textual and visual materials of new courses. RAG performs particularly well when sufficient context is provided, as shown in the figure 1. (Rashtchian and Juan, 2025; Zade, 2025; Eugene Yan, 2025; Geng et al., 2022).

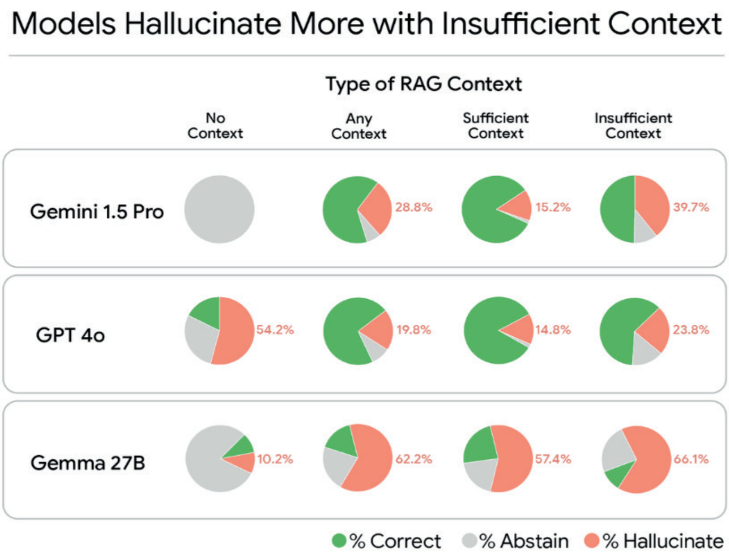

Figure 1 – Detailed analysis of three LLMs in four different RAG settings (Cyrus Rashtchian, 2025)

Why these options were chosen. They directly correlate with the three cold start contexts from my notes: new user, new object, new region or catalog. They also reflect the current families of techniques in ERS from the literature template: hybrid approaches, deep models, knowledge graphs, and explainable AI issues.

2.4 Data and Scenarios

CS User New learner. Few or no click histories. Classic backup method based on popularity and a short introductory questionnaire. Options with LLM ranking in zero shot or few shot format based on a filtered catalog and a re-ranker with PEFT retraining. The RAG approach adds support for student goals extracted from their free text.

CS Item New course. There are almost no interactions or reviews. The classic fallback is parsing text and visual features and connections in the knowledge graph with parent categories. Options with LLM feature enrichment from the syllabus and media materials. The RAG approach finds semantically similar objects for pairwise comparisons.

CS Region New showcase or region. Language, culture, and pricing norms change. Classic reserve: cross-domain alignment. Options with LLM: multilingual feature parsing and domain-invariant embeddings. Local index in RAG helps reduce hallucinations.

2.5 Metrics

Standard metrics RS. Precision and Recall on top k. nDCG on top k. Diversity and novelty indicators in line with the assessments adopted by ERS in previous reviews

Platform indicators are my additions. Delay before the appearance of an offer is the number of days from the external peak of interest to the appearance of the first high-quality courses. Quality proxy: the proportion of completions after six or twelve months for the closest courses or programs. Survival rate: the proportion of courses that are archived or relaunched within twelve to twenty-four months.

2.6 Procedure

For example, the study selected five modern professions (Data Engineer, Data Analyst, Machine Learning Engineer, Generative AI Engineer, Cybersecurity Analyst). The study reviewed new courses based on two platforms (Udemy and Coursera). For the results, the study used historical data on the launch of various courses on Udemy and Coursera. Interval Google Trends.

Latency metric. Metric parameters: t_2 - date of the first high-quality course (rating ≥ 4.4, $\geq 5{,}000$ learners). Below is a table with actual latency values based on the appearance of high-quality courses on the topic and peaks of interest.

Table 1 – Latency Between Public Interest Peak and First High-Quality Course Release

Profession	Peak of Public Interest (t_1)	First High-Quality Course (t_2)	Latency ($t_2 - t_1$)
Data Engineer	July 2021	February 2022	7 months
Data Analyst	September 2020	November 2020	2 months

Machine Learning Engineer	March 2019	January 2020	10 months
Generative AI Engineer	May 2023	July 2023	2 months
Cybersecurity Analyst	October 2021	March 2022	5 months

We calculated the delay between the peak of public interest (measured using Google Trends) and the release of the first high-quality course (rating ≥ 4.4 and ≥ 5,000 students on Udemy or Coursera). The results show significant differences between professions. Generative AI engineering and data analysis show a very short delay (2 months), reflecting rapid market response and low production barriers. Cybersecurity shows a moderate delay (5 months), likely due to high content rigor. Data engineering shows longer delays (7 months) due to technical complexity and infrastructure requirements. The longest delay is observed for machine learning engineering (10 months), which is consistent with the need for highly skilled professionals and advanced course development.

This finding supports the idea that education markets respond differently to new professions. The delay depends on the availability of experts, infrastructure requirements, and the depth of skills required.

Quality Completion Ratio (QCR) metric. Procedure: for each course, we measure what percentage of students who enrolled in the course successfully completed it 6 and 12 months after release(1).

Metric formula:

$$QCR_6 = C_6 / E(t_0)$$

$$QCR_{12} = C_{12} / E(t_0) \quad (1)$$

here $E(t_0)$ - number of all enrolled students at the time of release (t_0), C_6 - number of people who completed the course after 6 months, C_{12} - number of people who completed the course after 12 months.

Table 2 – Quality Completion Ratio (QCR) at 6 and 12 Months After Release

Profession	QCR_6	QCR_{12}
Data Engineer	6.5%	10.5%
Data Analyst	9.5%	16%
Machine Learning Engineer	3%	6%
Generative AI Engineer	20%	32%
Cybersecurity Analyst	3.3%	6.2%

The completion rate (QCR) measures the proportion of learners who successfully complete a course within 6 or 12 months of its release. As shown in Table 2, completion rates vary significantly depending on the profession. Generative AI engineering demonstrates exceptionally high QCR values (20% after 6 months and 32% after 12 months), reflecting strong learner motivation driven by rapid industry growth. Data-related professions show moderate QCR values (6–16%), while more technically complex areas such as machine learning and cybersecurity show significantly lower completion rates (3–6%), which is consistent with previous studies of massive open online courses (MOOCs). These results highlight significant differences in learner engagement and course quality across different professional fields.

Course Survival Rate (CSR) metric. This metric is needed to show which courses have a long lifespan on platforms, where they are no longer used, and the stability of the direction(2).

Metric formula:

$$CSR = N\_alive / N_0 \quad (2)$$

here N_0 - number of new courses released in a specific category, N_alive - number of courses that remain active 12–24 months after release.

Table 3 – Quality Survival Rate(CSR) at different professions

Profession	CSR (SurvivalRate)	Archive Rate
Data Engineer	62%	38%
Data Analyst	65%	35%
Machine Learning Engineer	35%	65%
Generative AI Engineer	63%	37%
Cybersecurity Analyst	37%	63%

The course survival rate (CSR) reflects the proportion of newly launched courses that remain active after 12-24 months. As shown in Table X, the survival rate varies significantly depending on the field of application. Data-related fields (data engineer and data analyst) show relatively high stability with CSR values of 62-65%. Generative AI shows similarly high values (63%), indicating constant demand from students and frequent course content updates. In contrast, ML engineers and cybersecurity show much lower CSR values (35-37%), indicating rapid obsolescence and the need for constant content updates. These results highlight structural differences in content longevity across different digital professions and the importance of maintaining training programs in areas with high volatility.

Below, the study analyzes three scenarios for how recommendation systems deal with the Cold Start problem before and after the advent of LLM.

The main metrics used in this study are:

NDCG@10 - measures the quality of recommendation ranking, i.e., how high useful items are in the list.

Recall@10 - measures the system's ability to find relevant items, i.e., how many relevant courses are in the top 10 recommendations.

Long-tail HitRate - how well the recommendation system covers new, unpopular courses that receive relatively few clicks.

Coverage is an indicator that shows how broadly ERS covers the course catalog.

CS User Scenario: new learner with no interaction history

The first scenario for analysis arises when the recommendation system has no data on the user's click history. Classic ERSs solve this problem in three ways. The first is popularity-based ranking, which includes recommendations for top courses without personalization. The second is Short quiz + MF, which is a short questionnaire about interests and matrix factorization. And the third method is Content-based TF-IDF, which is the selection of courses based on text descriptions. Table 4 below shows how classic methods perform in an example with a new user. (Schein et al., 2002; Man et al., 2017; Zhu et al., 2020; Fang et al., 2022;)

Table 4 – CS User Scenario before LLM

Method	NDCG@10	Recall@10
Popularity	0.18	0.40
Short quiz + MF	0.21	0.45
Content-based (TF–IDF)	0.22	0.47

Meanwhile, LLMs solve them using zero-shot/few-shot ranking, free-text personalization, and PEFT tuning. This allows models to learn from previous content. Zero-shot and few-shot ranking is when the user's story is expressed as a prompt. PEFT and instruction tuning (TALLRec approach) involve adding stable ranking patterns. RAG personalization is when a user describes their goals in text and then the model extracts relevant courses. Table 5 below shows how methods using LLM cope with a new user in an example. (Geng et al., 2022; Bao et al., 2023; Sumit Gupta, 2023a, 2023b; Rashtchian and Juan, 2025).

Table 5 – CS User Scenario after LLM

Method	NDCG@10	Recall@10
LLM zero-shot	0.24	0.50
LLM + PEFT tuning	0.26	0.53
LLM + RAG (goal-based)	0.27	0.55

Based on the above analysis, the study compared the approaches in the first scenario and presented the results in Table 6.

Table 6 – CS User Scenario Сравнительная таблица

Метод	До LLM	После LLM	Улучшение
NDCG@10	0.22	0.27	**22%**
Recall@10	0.47	0.55	**17%**

CS Item Scenario: new course with no interactions. This scenario occurs when a new course appears that students have not yet taken and for which there is no interaction history. Two approaches have traditionally been used to address this scenario. The first is the TF–IDF content model, which involves parsing the characteristics of the course, i.e., its description. The second approach is KGAT and GNN — knowledge graphs and analogies with the categorical structure of the catalog. Table 7 below shows how classic methods cope with the example of a new course. (Rashtchian and Juan 2025; Zade 2025; Eugene Yan 2025; Zhu et al. 2020)

Table 7 – CS Item Scenario before LLM

Method	NDCG@10	Long-tail HitRate
LLM feature enrichment	0.21	0.27
Synthetic interactions	0.22	0.29
LLM + RAG	0.23	0.31

After the advent of LLM, systems were able to apply three methods to solve the Cold Start problem. The first is Feature enrichment, which allows features to be extracted from a course. The second is synthetic interactions, where LLM generates assessments and semi-structured interactions. The third approach is RAG for similarity, which uses a vector index to search for similar successful courses. Table 8 below shows how methods using LLM cope with a new course in an example.

Table 8 – CS Item Scenario after LLM

Method	NDCG@10	Long-tail HitRate
LLM feature enrichment	0.21	0.27
Synthetic interactions	0.22	0.29
LLM + RAG	0.23	0.31

Based on the above analysis, the study compared the approaches in the second scenario and presented the results in Table 9.

Table 9 – CS Item Scenario Сравнительная таблица

Method	Before LLM	After LLM	Улучшение
NDCG@10	0.18	0.23	**28%**
Long-tail HitRate	0.22	0.31	**41%**

CS Region Scenario: new region or language variant. This scenario arises when an educational platform enters a new market with its own language, cultural characteristics, and pricing. Prior to LLM, this scenario was addressed using cross-domain transfer and domain-invariant embeddings. Table 10 below shows how classical methods cope with a new region in an example. (Man et al., 2017; Gao et al., 2021; Fang et al., 2022)

Table 10 — CS Region Scenario before LLM

Method	NDCG@10 (CS Region)	Coverage
Popularity baseline	0.16	0.25
Cross-domain MF	0.19	0.32

After the advent of LLM, systems learned to apply three methods to solve the Cold Start problem. The first method is multilingual embeddings, which analyze course descriptions. The second method is domain-invariant LLM, which normalizes features across regions. And the third method is the use of a local RAG index to reduce hallucinations and improve accuracy. Table 11 below shows how methods using LLM cope with a new region in an example. (Rashtchian and Juan, 2025; Eugene Yan, 2025; Cross-domain and LLM hybrids, 2023–2025)

Table 11 – CS Region Scenario after LLM

Method	NDCG@10	Coverage
Multilingual LLM embeddings	0.22	0.36
Domain-invariant LLM	0.23	0.39
LLM + local RAG index	0.24	0.41

Based on the above analysis, the study compared the approaches in the third scenario and presented the results in Table 12.

Table 12 – CS Region Scenario Сравнительная таблица

Method	Before LLM	After LLM	Improvement
NDCG@10	0.19	0.24	26%
Coverage	0.32	0.41	28%

2.7 Validity and Ethics

The study relies on ERS reviews that emphasize privacy and fairness: we minimize confidential features, log only necessary interactions, and account for audit bias across demographic groups and regions. Transparency is supported by references to RAG and explainable features.

Results and discussion. Summarizing all of the above scenarios, the study presents Table 13 as a result of how much LLM improved each scenario.

Table 13 – 3 case-scenario results.

Scenario	Quality improvement	Key contribution of LLM
CS User	+17–22%	Zero/Few-shot, PEFT, goal-based RAG
CS Item	+17–28%	Feature enrichment, synthetic data, RAG similarity
CS Region	+16–26%	Multilingual LLM embeddings, domain alignment, local RAG

Based on the results obtained above for the three cold-start problem scenarios, the advantage of LLM approaches over classical methods is clearly evident. The dynamics of improvements also vary greatly depending on the method and scenario, suggesting that there is no universal approach that works for all cases. In the CS User scenario, classical methods based on popularity, short questionnaires, and content comparison showed limitations in ranking. Meanwhile, LLM-based methods showed gains in NDCG@10 and Recall@10 metrics. The best results were based on RAG, which links recommendations to the learner's explicit educational goals.

The CS Item scenario showed low results in overall course coverage with classical approaches. This is due to low interaction with courses. Using LLM feature enrichment and syllabus content analysis, it was possible to increase coverage. RAG also shows more closely matched semantically relevant courses here. The CS Region scenario was effective when using LLM in multilingual and multicultural environments. Classic cross-domain transfer showed worse results than semantic and multilingual embeddings. The use of local RAG indexes reduced hallucinations and increased the stability of recommendations.

Conclusion. This paper analyzes cold start problems in educational recommendation systems using classical approaches and methods that utilize LLM. Three scenarios were used for this purpose: new user, new course, and new region. Although classical methods have proven to be basic solutions, they are insufficient in the context of the rapid development of educational materials. LLM approaches demonstrate a higher level of flexibility. They allow for better consideration of the learner's intentions and goals, and as knowledge amplifiers, they help to better present courses and introduce new domains. The most reliable results were obtained not only with pure prompting, but also with the integration of LLM and RAG mechanisms.

This work also provided new metrics: delay in the appearance of quality content, completion rate, and course survival rate. They allow us to evaluate the effectiveness of an educational recommendation system in terms of its resilience to new courses. Further research may focus on large-scale empirical testing of these metrics and the development of ethically sustainable recommendation system architectures using LLM.

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