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Smart Mcq Generator For Personalized Learning Paths Using Rag And Generative Ai

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ABSTRACT

In the development of more automated and adaptive learning environments, a large part of it is to use artificial intelligence in machine-generated multiple-choice questions (MCQs) generated from a combination of different sources. Therefore, we propose a novel intelligent Quiz Generator with which an educator can automatically generate multiple choice questions (MCQs) with high quality questions as well as contextually relevant and challenging questions. In the proposed system, we propose large language model with high quality questions and retrieval augmented generation (RAG) and some optimization techniques for prompt engineering for generating very high quality and contextually relevant quiz questions. A chain-of-thought and self-refine prompting techniques are applied for enabling the model to generate questions that not only are consistent with learning objective but also take into account the common student misconceptions. In addition, we apply performance matrix to support the analysis of individual learning progress of each student. The matrix takes into consideration the results of previous questions, which finds areas of strength and weaknesses, and adjusts future quizzes accordingly to foster accurate discovery of learning needs among students. Based on extensive evaluation we could conclude that the automated system can generate various and adaptive MCQs with higher engagement and comprehension of students. With the aid of artificial intelligence and adding performance analytics, this project provides a reliable and innovative solution for automatic quiz generation and moving forward Personalized.

Keywords—Student Misconceptions Analysis, Performance Analytics, Automated Quiz Generation, Student Engagement and Comprehension , Chain-of-Thought Prompting

I. INTRODUCTION

One of the growing needs in the modern educational environment is for customized and adaptive learning solutions. In this perspective, traditional quiz generation methods have large computing footprints and might not be able to meet the needs of diverse learning programs. In this paper, we present a personalized MCQ generator for adaptive learning solutions based on recreation-augmented generation (RAG) and generative AI. A large language model (LLM) of prompt engineering techniques — weighted learning prompting (WLP), chain-of-thought reasoning (CoT), and self-refine prompting — are used to produce high-quality, contextually relevant, and difficult multitude questions (MCQs). Unlike standard systems, it assesses quizzes for each individual student's quality on the basis of their pocket responses and the difficulty of the quiz. One of the important factors to consider is the performance model, which measures student progress with indicators to identify strengths and weaknesses on quizzes and adapt them to meet learning objectives. The AI system is designed to inspire student engagement, comprehension, and assistance, with a focus on developing personal learning. It eliminates manual instruction, thus permitting teachers to focus on teaching as well as initializing results and complementing curriculum guidelines across all academic levels and subjects. At the domain level, generative AI is a province in automating the explanation of context-MCQs. RAG continues in three stages: retrieval, generation, and refinement. In the retrieval step, the system searches for relevant information from curated knowledge sources. In the generation step, the LLM generates queries based on the retrieved information. In the refinement step, techniques such as weighted learning prompting (WLP) and self-refine are employed to ensure that the natural sequence of content is coherent and free of inaccuracies. This approach is used to create assessments that integrate adaptive learning with advertising techniques and natural language processing (NLP), or to develop a scalable, efficient, and adjustable replacement for contemporary educational frameworks.

2. EXISTING SYSTEM

Conventional MCQ question generation systems rely on manual question banks and fundamental NLP methods, rule-based structures, and manual biding with high human effort and low adaptability. Teachers typically have to manually select or generate questions, leading to low diversity at personalized contextual variance. The systems are typically static, not utilizing any external real-time knowledge updates, making them more ineffective in dynamic learning environments. Traditional MCQ generators use TF-IDF and Named Entity Recognition (NER) to perform keyword extraction and question formation. Even as Word2Vec and GloVe models provide related words and associations, they do not fully capture conceptual knowledge and sentence formation. Rule-based templates yield repeated syntactically wrong questions, thus lowering test quality. Text-based question generation with LSTMs and RNNs perform better, but long passages struggle with coherence. Newer frameworks like T5 and BERT enable question generation with automation, but again rely on pre-trained knowledge, uniting source material without information retrieval or needing current valid data. Most systems do not change the question stated within the prompt relative to the student's performance due to the lack of Weighted Learning Prompting (WLP) and Retrieval-Augmented Generation (RAG). As it currently stands, most MCQ-generating systems are insufficiently flexible, adaptable, or personalized, which warrants the development of AI-driven, dynamically adaptive systems.

3. PROPOSED SYSTEM

Advances in computing have led to groundbreaking research those can present significant differences in artificial intelligence. The "RAG Method for Personalized Quiz Generation for Adaptive Learning in Gen AI" is an artificial intelligence-based program that autonomously generates multiple-choice questions (MCQs). By the union of a large language model (LLM) and retrieval-augmented generation (RAG) and prompt engineering, it is possible to design high-quality, contextually appropriate questions. Afterward, the adaptive quizzes are created based on the students' teaching levels thus being able to not only eliminate errors in students' knowledge but also save quiz development time considerably. Furthermore, a performance matrix, used as a tool in this case, can be very helpful for determining how well or poorly students are doing and what should be done in the future in order to help them learn better. The question area involves the system in the assessment consisting of the types of MCQs: math-based, concept-based, and coding-based. At the same time, to enable the successive., innovative adaptability, accurateness, and the effectiveness of the learning process. This then leads to the conclusion of eliminating numerical precision, question difficulty, and code verification as challenges, and thus making it possible for the learning experience and participation to be improved.

4. RELATED WORKS

[1] Based on a study by Harshada Patil., et al. (2023), an automated system for creating Multiple-Choice Questions (MCQs) has been developed using NLP techniques. This system summarizes the input text using the BERT algorithm and then performs sentence planning to produce MCQs. Distractors for the MCQs have been generated using WordNet. Through automation the problem of manual question creation has been overcome making it easier and cheaper to create questions. Efficient summarizing of text and generation of relevant distractors have been done to help making assessment process faster and effective especially in online learning environments.

[2] Prajakta, J. K., Sunder, R. S., et al (2021) propose a novel approach for abstract classification that captures contextual information relating to the content of the document: A focus-based conceptualisation of an abstract is possible by extracting relevant associated terms. To achieve this goal, contextually relevant relevant words

are used to categorize abstracts. A systematic comparative study on their performance showed that context-based classification greatly improved document classification accuracy, and further helped to reveal contextual information which would be necessary to make accurate decisions. The paper also discusses ongoing research related to Automatic Question Generation (AQG) via Natural Language Processing (NLP). Context-based questions generation is being researched in several languages, including English, Punjabi, and Chinese.

5. INDENTATIONS AND EQUATIONS

The performance evaluation of MCQ generation systems typically relies on several key metrics to assess their effectiveness. Based on the provided paper, the evaluation considered five core criteria:

1. **Grammatical Fluidity (GF)** – Measures the correctness and coherence of the generated question.
2. **Answerability (A)** – Ensures the question has a valid and logically deducible correct answer.
3. **Diversity (D)** – Evaluates the variation in generated questions across topics.
4. **Complexity (C)** – Assesses the cognitive challenge of the question.
5. **Relevance (R)** – Checks if the question aligns with the intended topic.

These metrics are scored on a **scale of 1 to 5,** where **1 = poor** and **5 = excellent.**

1. Average Score Formula for Each Metric

Each metric's average performance is calculated as:

$$\text{Avg. Score} = \frac{\sum_{i=1}^{n} S_i}{n}$$

Where:

- SiS_iSi is the score assigned by an evaluator.
- nnn is the total number of evaluators.

For example, if three evaluators score **Grammatical Fluidity** as 4,5,44, 5, 44,5,4, then:

$$\text{GF Avg.} = \frac{4+5+4}{3} = 4.33$$

2. Overall Performance Score (OPS) Formula

To assess the overall performance of the system across all metrics, we compute:

$$OPS = \frac{GF + A + D + C + R}{5}$$

Where:

- GFGFGF = Grammatical Fluidity
- AAA = Answerability
- DDD = Diversity
- CCC = Complexity
- RRR = Relevance

For example, if the average scores are:

- GF=4.2GF = 4.2GF=4.2
- A=3.8A = 3.8A=3.8
- D=3.5D = 3.5D=3.5
- C=3.7C = 3.7C=3.7
- R=4.5R = 4.5R=4.5

Then:

OPS=4.2+3.8+3.5+3.7+4.55=3.94OPS = \frac{4.2 + 3.8 + 3.5 + 3.7 + 4.5}{5} = 3.94OPS=54.2+3.8+3.5+3.7+4.5=3.94

3. Question Type Performance Formula

To compare performance across question types (Math-Based, Concept-Based, Coding-Based), we calculate an average performance score per category**:**

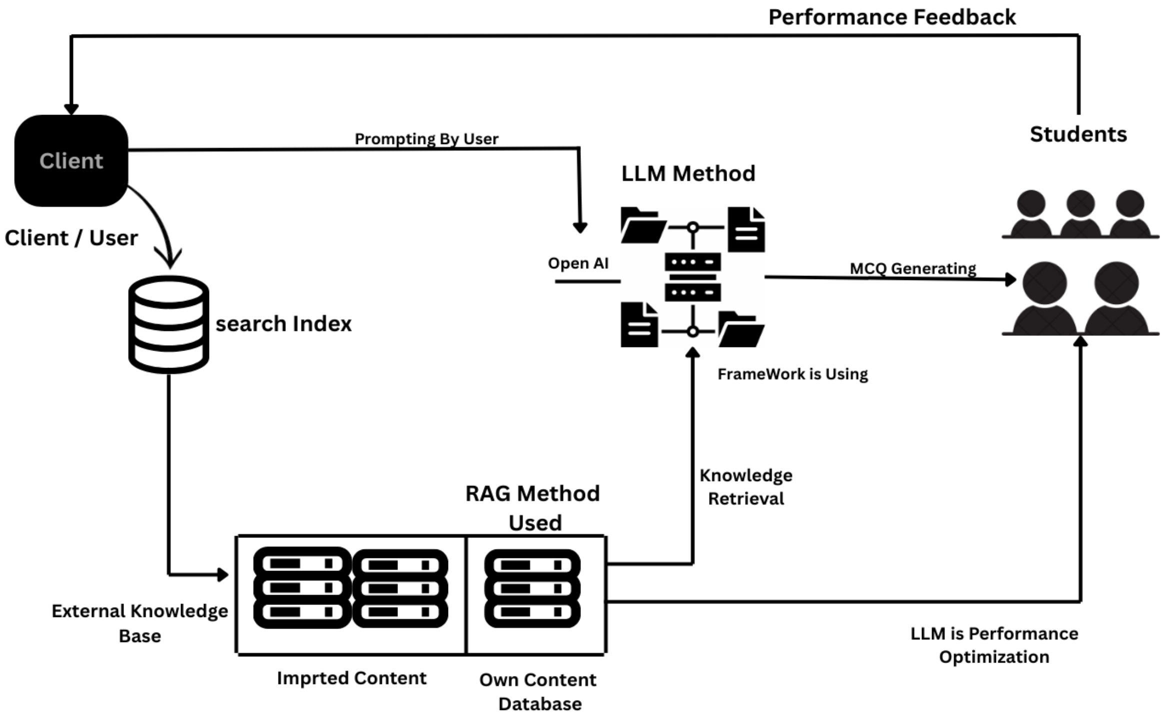
$$QPS_t = \frac{\sum_{m=1}^{M} OPS_m}{M}$$

Where:

- QPStQPS_tQPSt = Question Performance Score for a specific type ttt (Math, Concept, or Coding).
- OPSmOPS_mOPSm = Overall Performance Score for each question in that category.
- MMM = Total number of questions evaluated in that category.

6. FIGURES AND TABLES

Figure 4.1 LLM and RAG Algorithm.



Among the technical achievements, the Quiz Generator is an application of retrieval-augmented generation (RAG)and prompt engineering optimization for the formation of specific and relevant. This is achieved through the generator that first reads the educational material out of a predefined knowledge base and without delay utilizes a large language model (LLM) with a line of thought. The learning profilestudentrecords the results of their responses, thereby, teachers are encouraged to adjust the level difficulty of the test, addressing the students' weak areas and encouraging the strong ones. As a result, the adapted system provided quizzes are uniquely designed to create an environment that presents the learning of different students; thus, the system has opened doors for more students to participate in the process of learning, leading to improved understandings. This method, not only is the least work for the teacher, yet, also, it ensures that learning is fully optimized in the online and blended settings.

These 6 Steps are the basis for the whole operation and are presented in a summary form

RAG WORKING ALGORITHM.

Step 1: User Submits Topic For generating quiz questions a user has to submit a topic.
Step 2: Gather Relevant Material The system identifies the proper study materials by searching.
Step 3: Create MCQsThe AI software makes questions options from the resources at hand.
Step 4: Display Quiz & User Participation A test is performed, and the user responds to multiple questions.
Step 5: Evaluate Performance The results of the user are checked by the system.
Step 6: Modify & Enhance When the user has difficulties, the system decreases the level of difficulty; if they are successful, it makes the level more difficult so that they can learn better.

Result Analysis

Table 1. Personalization & Adaptive Learning (PAL). Comparison Table

Parameter	Existing System	Proposed System
Personalization Accuracy (%)	**60.08%** (Fixed question sets)	**89.01%**(student-based adaptation)
Question Difficulty Adjustment (%)	**50.09%** (Predefined levels)	**95.02%** (Real-time difficulty scaling)
Feedback Utilization (%)	**40.33%** (Limited improvements)	**85.02%**(Learner data refines questions dynamically)
Engagement Rate (%)	**65.12%** (Fixed assessments)	**91.22%** (Personalized & adaptive learning)

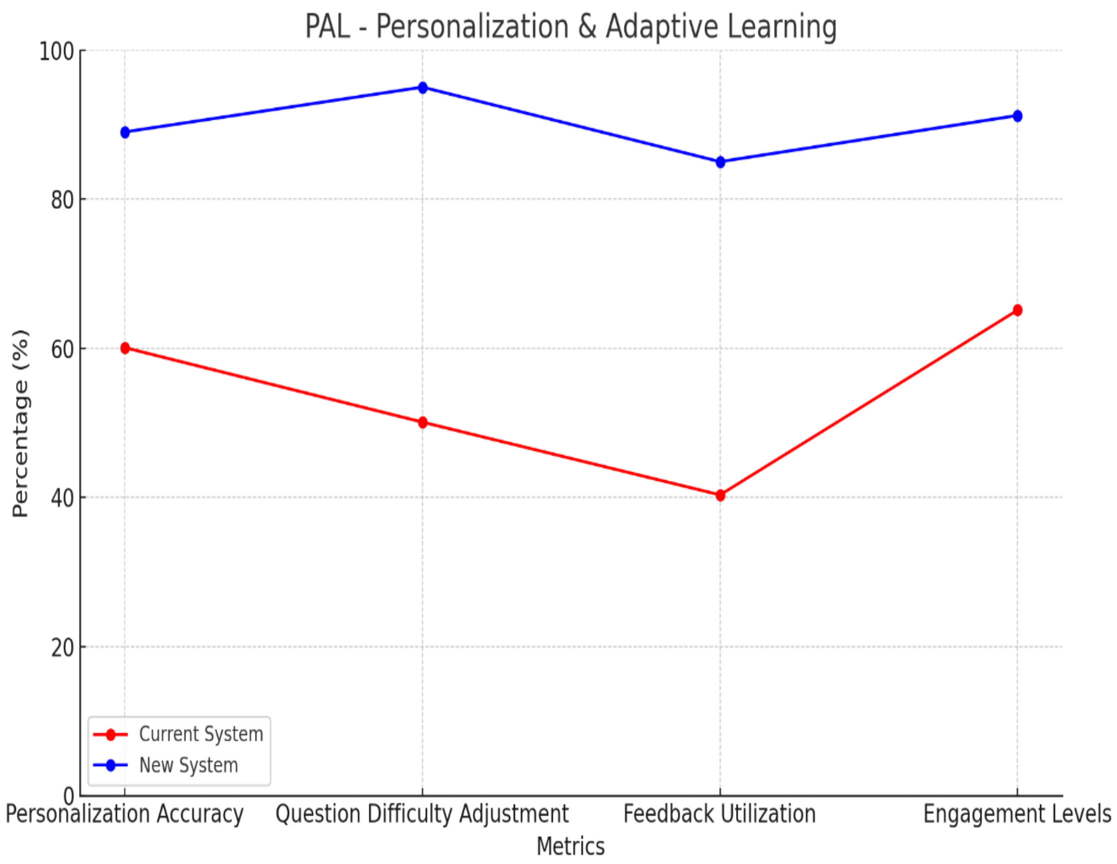


Figure 2. Comparison graph

The Personalization and Adaptive Learning (PAL) proposed system is extremely different from the current one. The new system is a revolution in its field, it represents a significant change in PAL, which is characterized by the recognition of the boundaries of the familiar and the search for new knowledge, in the first place, the correctness of the proposed systems' recommendation is equal to 89.01%, significant improvement over existing systems with the same accuracy of 60.08%, is possible through the algorithm's flexibility and student-centered suggestions base rather than a static one. Besides, it is modified and transformed in a way that it can also follow the real-time update of questions, raising the difficulty level from the former 50.09% to the impressive 95.02% while the past one has not reached this fraction. Also, the system is a breakthrough in the monitoring of the feedback usage as it exhibits a 85.02% improvement in the usage of feedback through continuously optimized learner data, compared to a 40.33% increase in the usage rate of the system. Hence, a personal touch and flexibility help in the rise of the levels of engagement both to 91.22% and 65.12%, respectively, the beliefs of the rising action in the static area are believed to be outdated. The underlying philosophy is the adaptation of the learning environment to suit the needs of students keeping them interested and focused throughout the learning journey. The new system not only integrates technology and education effectively but is also an example of how the system identifies the limitations and interests of the students and provides them with the appropriate knowledge, therefore feeding their inner motivation to complete their studies successfully. To add, these improvements are a great way to ensure personalized and adaptive learning experiences at the same time ensures that various learner needs are being covered while the potential of personalization and adaptability is being realized. Additionally, the emerging system underlines that e-learning would be much more intuitive, flexible, and student-cantered.

7. CONCLUSION

In conclusion, the AI-Powered Quiz Generator transforms MCQ automation, outperforming existing systems with (RAG), and prompt engineering methods. Unlike traditional quiz generators that are based on fixed question banks or pre-trained models with poor adaptability, our system generates high-quality, contextually appropriate, and logically consistent questions while handling frequent student misconceptions. Incorporating a performance matrix further maximizes personalized learning by adapting quizzes constantly based on individual performance. By lowering the workload of teachers considerably and implementing adaptive tests, this AI-powered solution advances online learning by making it a brighter, more effective, and more scalable way to create quizzes as opposed to old methods, developing more engaging and productive learning environments.

8. FUTURE WORK

Future evolution of the AI-driven Quiz Generator will concentrate on overcoming existing limitations and improving personalization accuracy. Sophisticated machine learning methods, such as reinforcement learning and adaptive algorithms, will be used to improve difficulty scaling and further personalize quizzes to a student's needs. Improved natural language processing (NLP) and cognitive modelling will offer better insights into student misconceptions, allowing more accurate question creation. Also, the combination of multimodal learning analytics, like response time and behavioural data, will result in a more interactive and dynamic test-taking process. These advances will make the system more intelligent, adaptive, and able to better maximize learning outcomes for students, resulting in a more effective and personalized learning tool.

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