

AI Assisted Mock Test for Self Improvement of Candidates in Bank Exam

Bhavani R.¹; Sudharsan P.²; Vishwa M.³; Shahul Hameed S.⁴; Muthusivam P.⁵

^{1,2,3,4,5}Department of Computer Science and Engineering, Government College of Engineering Srirangam, Tamilnadu, India

Publication Date: 2026/04/18

Abstract: Bank examinations require high accuracy, speed, and strong conceptual understanding in quantitative aptitude, reasoning ability, English language, and general awareness. Traditional mock examination systems provide static question banks and limited analytical feedback, which restrict adaptive learning and lacks personalized learning. This paper proposes an AI based mock examination system for bank exam preparation using agentic AI. The system integrates artificial intelligence techniques for dynamic question generation, automated evaluation, adaptive difficulty control, time management analysis, and personalized feedback delivery. The Large Language Model enhances contextual understanding and generates intelligent performance insights. Experimental analysis demonstrates improved learning efficiency, enhanced time optimization, and accurate readiness prediction. The proposed system transforms conventional mock testing into an intelligent adaptive preparation platform.

Keywords: Artificial Intelligence; Mock Examination; Bank Exam; Large Language Model; Adaptive Testing, Performance Analytics.

How to Cite: Bhavani R.; Sudharsan P.; Vishwa M.; Shahul Hameed S.; Muthusivam P. (2026) AI Assisted Mock Test for Self Improvement of Candidates in Bank Exam. *International Journal of Innovative Science and Research Technology*, 11(4), 983-987. <https://doi.org/10.38124/ijisrt/26apr676>

I. INTRODUCTION

This Competitive banking examinations conducted by the Institute of Banking Personnel Selection, State Bank of India, and Reserve Bank of India demand rigorous and well-structured preparation strategies due to their highly competitive nature and vast syllabus coverage. They evaluate candidates across multiple domains, including quantitative aptitude, reasoning ability, english language proficiency, and general awareness, requiring not only knowledge but also speed, accuracy, and strategic thinking.

However, most existing mock examination platforms suffer from significant limitations, as they rely on static datasets and rigid evaluation mechanisms, providing identical question sets to all users regardless of their individual skill levels. Such one-size-fits-all approaches fail to address the diverse learning needs of aspirants, resulting in inefficient preparation and lack of targeted improvement. Furthermore, these systems offer minimal analytical insights and lack the capability to deliver meaningful, personalized feedback, thereby limiting a candidate's ability to identify weaknesses and optimize performance effectively.

With the rapid advancement of Large Language Models, new opportunities have emerged in the field of intelligent educational systems. These models possess advanced capabilities such as contextual reasoning, semantic

understanding, and dynamic response generation, enabling the creation of adaptive and interactive learning environments. Leveraging these capabilities can significantly transform traditional exam preparation methods into more personalized and data-driven experiences.

In this context, this research proposes an AI-based mock examination system powered by a Large Language Model to enhance adaptive learning and improve performance in bank exam preparation. The proposed system aims to dynamically generate questions based on user proficiency, provide real-time feedback, and deliver detailed performance analytics, thereby enabling a more efficient, personalized, and outcome-oriented preparation process.

Additionally, the system seeks to bridge the gap between traditional assessment methods and intelligent learning frameworks by incorporating continuous performance monitoring and student performance analysis. By identifying learning patterns and forecasting potential outcomes, the system can guide aspirants with tailored recommendations, ultimately increasing their chances of success in competitive banking examinations.

II. RELATED WORK

The recent research paper based on the artificial intelligence exam evaluation examines how artificial

intelligence can improve exam evaluation by automating grading and assisting human evaluators. It uses techniques like image processing, handwriting recognition, and NLP models to assess both objective and subjective answers. Results show high accuracy, with over 94–97% consistency for objective questions and strong correlation (>0.7) with human grading for essays. Overall, AI-based evaluation is reliable, reduces workload, improves fairness, and enhances efficiency in the grading process [1].

The system present a comprehensive review of automatic question generation systems in education, analyzing their techniques, datasets, and evaluation methods. The study highlights that most automatic question generation approaches rely on natural language processing, templates, and increasingly deep learning models to generate questions from text. It identifies key challenges such as maintaining question quality, relevance, and diversity, along with limited evaluation standards. Overall, the paper concludes that automatic question generation has strong potential to support personalized learning and assessment, but requires further improvement in accuracy and instructional effectiveness.[2]

An AI-based system was designed to improve competitive exam preparation by analyzing student performance and providing personalized feedback. It uses machine learning techniques to track user responses, identify strengths and weaknesses, and generate customized study recommendations. The system helps learners focus on weak areas, improves learning efficiency, and supports adaptive preparation strategies. Overall, it demonstrates how AI can enhance exam readiness through data-driven insights and individualized guidance [3].

Large Language Models were used to automatically generate and evaluate multiple-choice questions from university-level materials. It demonstrates that LLMs can create relevant questions and also assess their quality based on correctness, clarity, and difficulty. The study finds that while LLM-based systems are effective and scalable, challenges remain in ensuring accuracy and avoiding ambiguous or misleading questions. Overall, it shows strong potential for automating assessment creation in higher education [4].

An advanced AI-based learning system that uses large language models to automatically generate multiple-choice questions, evaluate answers, and analyze student performance was designed [5]. The system not only creates relevant MCQs from study material but also provides instant feedback and tracks learner progress to identify strengths and weaknesses. It enhances personalized learning by adapting to individual performance and improving exam preparation efficiency. Overall, the study highlights the effectiveness of LLMs in building intelligent, automated assessment and learning systems.

It is observed from the literature that there are systems available for automatic question generation and evaluation. Current researches focus on feedback based self-improvement of candidates. So, this paper aims to develop

an AI based system that generates questions for self-improvement of the candidates based on their previous performances.

III. MATERIALS AND METHODS

The system architecture of the AI based mock examination system for bank exam is given in Fig 1. The proposed AI integrated mock examination system for banking exams follows a modular architecture designed to automate question generation, answer evaluation, and performance analysis. The architecture consists of several interconnected components that ensure secure access, intelligent question generation, automated assessment, and personalized feedback for users.

The system begins with the user layer, here the student/candidate interacts with the platform through a web interface. This interface acts as the primary access point for candidates to register, log in, attempt mock tests, and view their performance reports. The interface is designed to be user friendly and accessible across different devices.

To ensure secure access, the system integrates email authentication. Users can sign in using their Google credentials, which simplifies the login process while maintaining security. At this stage, the system categorizes users into new users and existing users. New users are required to register their details, while existing users can directly access their dashboard and previous performance records.

Once authenticated, the user proceeds to the mock test module. If the user is new user the system provides some set of questions to analyse the strength and weakness of the user. Once after completing the sample test the performance in the sample test would be considered for analysing the strength and weakness of the user, after completing the sample test the user would be considered as existing user. In the case of existing user the system will analyse the previous performance of the user and provides more number of questions in the weaker area in order to improve the weaker areas. These questions are dynamically generated using the Ai engine question generator, which leverages artificial intelligence models to create varied and relevant questions aligned with the Banking examination pattern. This approach ensures that each mock test is unique and helps candidates in personalized improvement in the areas that they are weak.

After the user submits responses, the system activates the answer evaluation module. This module automatically checks the candidate's responses against the correct answers stored in the system or generated by the AI engine. The evaluation process calculates scores, accuracy levels, and other relevant metrics. Following answer evaluation, the system performs performance analysis. In this stage, the system analyses the candidate's performance based on multiple parameters such as accuracy, topic-wise performance, time taken per question, and overall score. This analysis helps identify the strengths and weaknesses of the candidate.

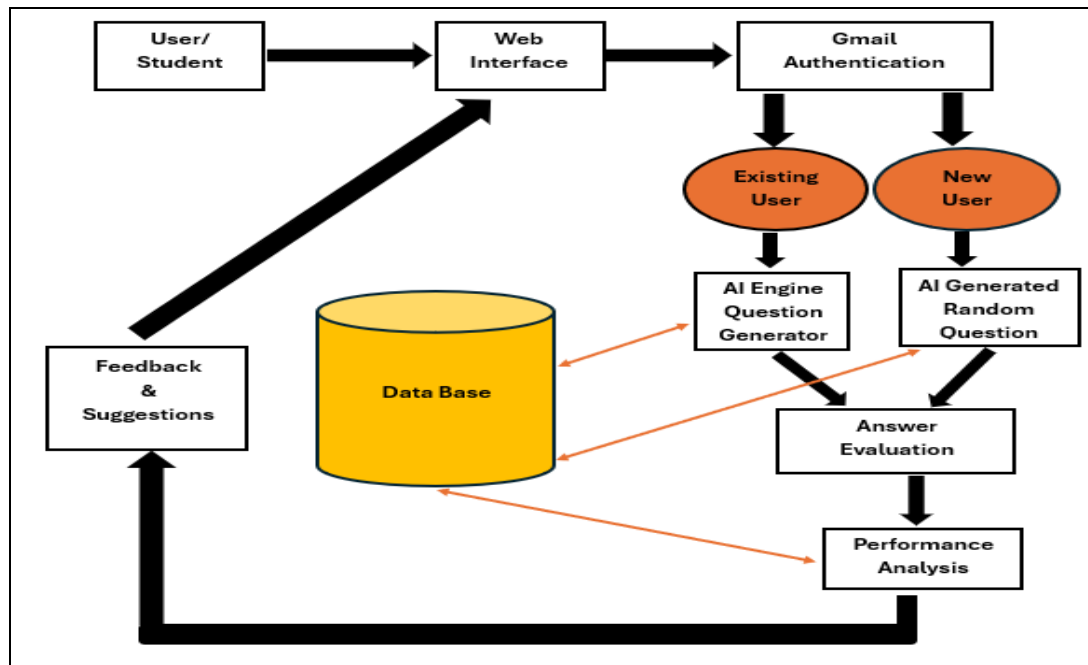


Fig 1 Proposed System Architecture

The strength and weakness of the candidate is identified by calculating the accuracy and number of questions answered against the number of question in particular section. After analysing the performance, the performance will be stored in the database, which will be used by the user to identify the strength and weakness of the user to provide the questions.

Finally, the system generates feedback and suggestions. Using AI-based analytics, the platform provides personalized recommendations, highlighting areas that require improvement and suggesting practice strategies. This feedback helps candidates focus on weaker sections and improve their preparation for competitive exams.

Overall, the proposed architecture ensures secure user authentication, intelligent question generation, automated evaluation and personalized learning platform, thereby creating an efficient and adaptive mock examination platform for banking exams. The proposed AI based mock examination system consists of the following modules.

➤ *Dynamic Question Generation Module*

The Large Language Model generates topic specific questions for: Arithmetic and data interpretation, logical reasoning and puzzles, English grammar and comprehension, banking awareness and current affairs. The system ensures alignment with current bank exam patterns and generates question based on the previous performance of the user. The model analysis the strength and weakness of the user based on the previous performance of the user and provides more question in the weaker section in the upcoming tests to improve their performance in their weaker areas. This is how this model bridges the gap of traditional mock exam.

➤ *Automated Evaluation Module*

Objective questions are evaluated automatically through answer matching. For descriptive questions, the Large

Language Model performs semantic comparison between candidate responses and model answers to assess conceptual understanding.

➤ *Time Management Analysis*

Time efficiency is a critical factor in bank exams. The system calculates:

$$\text{Accuracy Rate} = \frac{\text{Correct Answers}}{\text{Total Questions}} \tag{1}$$

$$\text{Time Efficiency} = \frac{\text{Ideal Time}}{\text{Total Questions}} \tag{2}$$

Overall performance index P is computed as: P = 0.6 accuracy rate + 0.4 time efficiency. This metrics predict exam readiness.

➤ *Personalized Feedback*

The proposed system generates structured feedback which includes: Section wise strengths and weakness and areas to improve and where the students lacking in the race, topic wise weakness, conceptual error explanations and recommend improvement strategies.

➤ *Implementation*

The proposed AI-integrated mock examination system was implemented using a combination of standard hardware, modern web technologies, and large language model integration to ensure efficiency, scalability, and adaptability. The proposed model was developed with a computer system equipped with an Intel core i3 processor and 8 GB of RAM, demonstrating that the application can function effectively on moderate computing resources without requiring high-end infrastructure. Since the computationally intensive tasks, particularly AI-based question generation, are handled

through external services, the local system requirements remain minimal.

The software development process was carried out using Visual Studio Code as the primary coding environment. The frontend of the application was built using React along with Next.js, enabling the creation of a dynamic, responsive, and user-friendly interface. These technologies support component-based development, which improves maintainability and allows efficient rendering of test interfaces, performance dashboards, and feedback modules. Data exchange between different components of the system is handled using JSON format, ensuring lightweight and structured communication.

A key aspect of the implementation is the integration of the Large Language Model Gemini 2.5 Flash, which is responsible for automatic question generation. The model is accessed through the Genkit library, which simplifies interaction with AI services and manages prompt structuring. Based on user performance data such as previous scores, weak subject areas, and response accuracy, the model generates customized question sets with varying difficulty levels.

For data storage and management, the system utilizes MySQL as the backend database. The database is designed to store user profiles, test records, question attempts, and detailed performance metrics including accuracy, time taken,

and topic-wise analysis. This structured storage enables efficient retrieval of user historical data, which is essential for generating personalized tests and conducting performance analysis.

The overall system workflow is designed to ensure seamless interaction between components. When a user logs into the system, their previous performance data is retrieved from the database and sent to the AI module through Genkit. The AI model then generates a tailored set of questions, which are presented to the user via the frontend interface. After the test is completed, the responses are evaluated and analyzed to compute performance metrics and stored in the database. Based on this analysis, the system generates detailed feedback and recommendations, which are displayed to the user. This integrated approach ensures continuous assessment, personalization, and improvement, making the system highly effective for bank exam preparation.

IV. RESULTS AND DISCUSSIONS

The proposed AI integrated mock examination system was developed and evaluated to assess its effectiveness in providing adaptive learning and personalized test experiences for bank exam aspirants. The system successfully demonstrated its ability to generate dynamic question sets, analyze user performance, and deliver meaningful feedback based on individual performance.

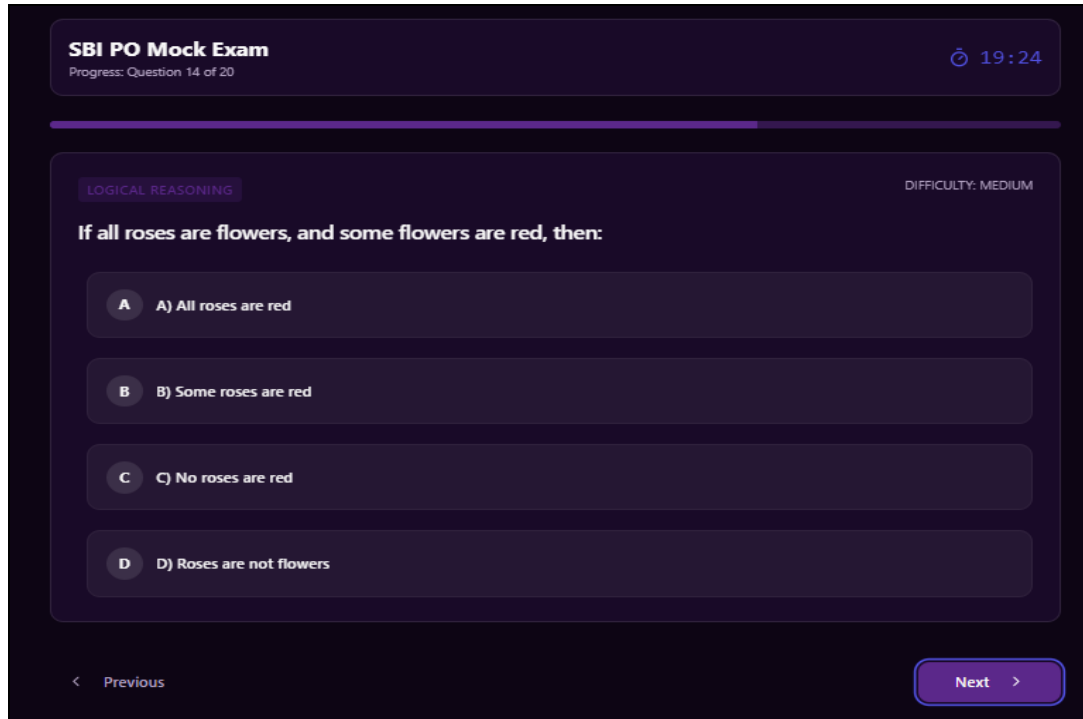


Fig 2 AI Generated Question

During testing, the integration of the Large Language Model Gemini 2.5 Flash enabled efficient and context-aware question generation. The model produced relevant and varied questions across different sections such as quantitative aptitude, reasoning, and English. It was observed that the

generated questions aligned well with the difficulty level required for bank examinations, and the system was capable of adjusting question complexity based on the user's prior performance. The question generated using the Large Language Model was shown in the Fig 2.

The Fig 3 shows the performance of the user in the mock test ,which includes the percentage of mark he scored in the test and the sectional marks scored by the student in the three subjects English, quantitative aptitude and logical reasoning and also the system will generate the AI performance feedback , in the figure 3 the proposed system generated the

feedback that the student needs improvement and suggested to improve weaker areas and the weaker areas are mentioned in the recommendation for student. This is how this model built, bridges the gap of existing static mock test and provides personalized learning platform for the user.

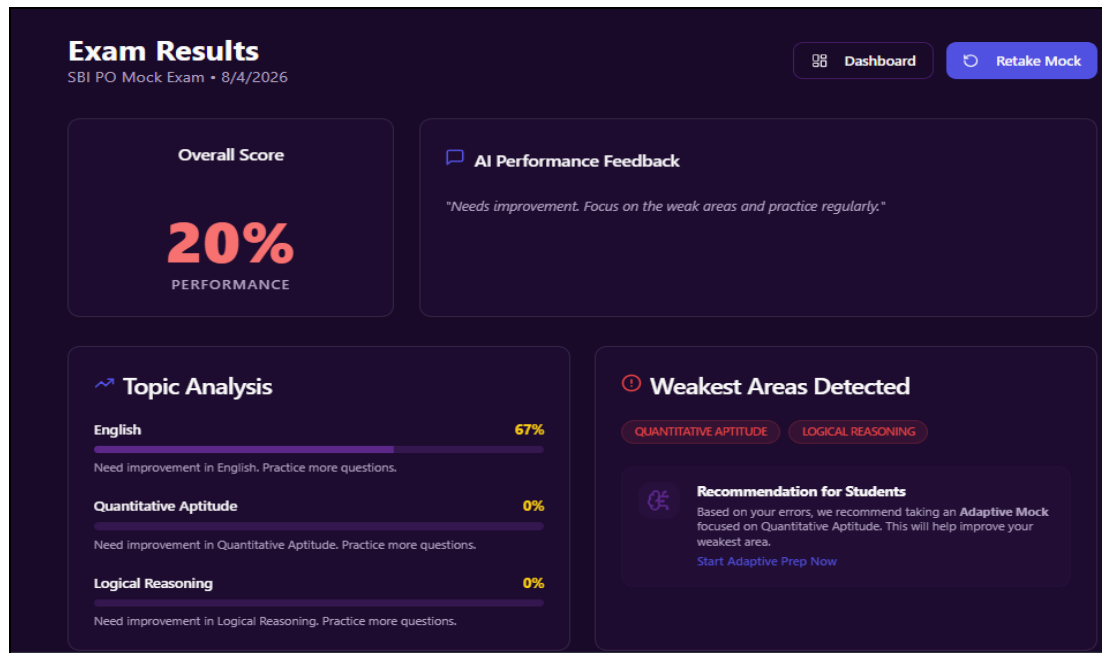


Fig 3.Result Page

V. CONCLUSION

In this study, an AI based system for bank exam preparation, leveraging the capabilities of the Gemini 2.5 Flash large language model to generate dynamic and adaptive question sets was proposed. Unlike conventional static mock tests, the proposed system personalizes question sets based on the previous performance of the user, ensuring that learners are continuously challenged at an appropriate difficulty level. This adaptive mechanism not only enhances engagement but also supports targeted learning by identifying individual strengths and weaknesses. Furthermore, the system provides immediate, context-aware feedback, enabling users to understand their mistakes and improve more effectively. The integration of real-time question generation and personalized feedback demonstrates the potential of modern LLMs in transforming traditional exam preparation methodologies into intelligent, learner-centric systems.

REFERENCES

- [1]. Yuwei Li, 2024. The Application of Artificial Intelligence in Exam Evaluation. The 4th International Conference on Machine Learning and Big Data Analytics for IoT Security and Privacy, Procedia Computer Science, 243, pp.1222-1230.
- [2]. Kurdi, G., Leo, J., Parsia, B., Sattler, U. and Al-Emari, S., 2020. A systematic review of automatic question generation for educational purposes. International journal of artificial intelligence in education, 30(1), pp.121-204.

- [3]. Gnanasigamani, L.J., Ruby, D., Harish, B., Vajrala, H. and Sanjai, K., 2025, July. AI-Powered Performance Analysis and Personalized Feedback System for Competitive Exam Preparation. In 2025 International Conference on Sensors and Related Networks (SENNET) Special Focus on Digital Healthcare (64220) (pp. 1-6). IEEE.
- [4]. Mucciaccia, S.S., Paixão, T.M., Mutz, F.W., Badue, C.S., de Souza, A.F. and Oliveira-Santos, T., 2025, January. Automatic multiple-choice question generation and evaluation systems based on LLM: A study case with university resolutions. In Proceedings of the 31st International Conference on Computational Linguistics (pp. 2246-2260).
- [5]. Snegaa, A., Sabiyath Fatima, N., Karthiga, I., Amsavalli, S., Nazreen, A. and Jhasim Hassan, J., 2025, February. Advanced Learning System—Automatic MCQ Generator with Answer Evaluation and Performance Analysis Using LLM. In International Conference On Innovative Computing And Communication (pp. 607-622). Singapore: Springer Nature Singapore.