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Quantum - Assisted AI Interview Intelligence and Placement Readiness Platform

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ABSTRACT:

Campus placements play a prominent role in student's career. Many students find it challenging to prepare effectively for interviews due to the absence of adaptive mock interview platforms and personalized performance analysis. However, existing platforms primarily focus on aptitude and coding assessments, offering limited support for comprehensive interview preparation. This project proposes a Quantum-Assisted AI Interview Intelligence and Placement Readiness Platform that conducts adaptive technical and HR interviews based on a student's resume, skills, projects, and target job role. The system employs an AI interviewer to generate dynamic follow-up questions and includes coding assessments with an integrated code editor supporting multiple programming languages. Candidate responses are analyzed using Natural Language Processing, speech processing, and visual analysis to evaluate technical knowledge, coding performance, communication skills, project understanding, and behavioral indicators. Based on the assessment, the platform generates personalized feedback and interview-readiness reports. Quantum Approximate Optimization Algorithm (QAOA) is used in this system to optimize personalized interview preparation paths by considering individual performance, skill gaps, target role, and available preparation time. This enables adaptive learning and enhances student's readiness for campus placement interviews.

Keywords: *AI Interview, Adaptive Interviewing, Coding Assessment, Candidate Selection, Quantum Optimization*

1. INTRODUCTION:

Campus placements play an important role in shaping student's career opportunities by providing a pathway from academic learning to professional employment. However, preparing for placement interviews can be challenging, even for students with strong academic records. Interviews require more than theoretical knowledge and good grades. Students must be able to explain technical concepts, solve problems, discuss their academic projects, communicate clearly, and respond confidently to different questions. Many students struggle because they have limited opportunities to practise in a realistic interview environment. As a result, there is a need for an effective preparation system that helps students identify their weaknesses, improve their skills, and develop confidence before attending actual placement interviews.

Several online platforms support placement preparation through aptitude tests, programming exercises, coding assessments, and learning resources. These platforms help students strengthen their problem-solving abilities and improve their understanding of technical subjects. However, interview preparation involves additional skills that cannot always be developed through independent practice alone. In a real interview, candidates must explain their answers, respond to follow-up questions, justify their decisions, and discuss their projects in detail. They may also face HR questions related to teamwork, strengths, weaknesses, career goals, and workplace situations. Existing preparation methods may not provide sufficient personalized practice across all these areas. Therefore, an intelligent platform that combines technical interviews, HR interactions, coding practice, and performance feedback can help address these limitations.

Artificial Intelligence (AI) offers useful techniques for making interview preparation more interactive and personalized. AI-based systems can process information, generate relevant questions, analyze responses, and provide feedback according to defined evaluation criteria. Natural Language Processing (NLP) can support the analysis of candidate answers, while speech to-text and text-to-speech technologies enable voice-based interaction. These technologies allow students to practice answering questions naturally instead of relying only on written exercises.

The proposed Quantum-Assisted AI Interview Intelligence and Placement Readiness Platform aims to provide students with a personalized environment for practicing technical and HR interviews. The platform uses information from a student's resume, including educational qualifications, technical skills, projects, and experience, along with the target job role. This information helps the system generate questions relevant to the student's background and career interests. For example, a student whose resume includes Python, database management, and a machine learning project may receive questions about programming concepts, database operations, and project implementation. The system can also ask follow-up questions based on previous responses to examine the candidate's understanding of a topic. This approach encourages students to develop conceptual clarity and explain their knowledge rather than simply memorize answers.

The platform supports voice-based interviews using speech-to-text (STT) and text-to-speech (TTS) technologies. Speech-to-text converts the candidate's spoken answers into text for evaluation, while text-to-speech enables the AI interviewer to present questions through audio. This creates a more natural interview experience and reduces the need for candidates to type every response. The system can also examine selected communication indicators, such as speaking rate and filler-word usage, to provide suggestions for improvement. These indicators are intended to support communication practice and should not be treated as definitive measurements of a person's personality or confidence.

Another important feature is the integrated coding interview environment. Technical interviews often require candidates to solve programming problems, write code, and explain their approach. The platform allows students to answer coding questions using a selected programming language and execute their solutions through an integrated code execution service. Coding performance can be evaluated using execution results, test cases, and relevant correctness criteria. This feature helps students practice technical problem-solving within the same environment used for their interview preparation. It also complements theoretical assessment by examining the candidate's ability to apply programming knowledge to practical problems. The platform evaluates interview performance across multiple dimensions, including technical knowledge, coding ability, project understanding, communication, and selected behavioral and speech-related indicators. Technical answers are assessed based on their relevance, correctness, and completeness. Coding solutions are evaluated using the available execution and testing mechanisms, while project-based questions examine the student's understanding of their own work. Communication feedback focuses on selected measurable aspects of spoken responses. Based on these assessments, the system generates a personalized report containing performance scores, strengths, areas requiring improvement, and recommendations for further practice. The purpose is to support individual learning rather than rank students or assign them to particular job roles.

The quantum-assisted component focuses on optimizing the selection of follow-up questions and preparation priorities. Students have different skill levels, learning needs, target roles, and amounts of time available for preparation. A fixed preparation plan may not address these differences effectively. The Quantum Approximate Optimization Algorithm (QAOA) is considered for exploring suitable combinations of questions or preparation activities based on factors such as skill gaps, previous performance, question difficulty, topic coverage, target role, and available preparation time. The optimization problem is defined using an objective function and relevant constraints to identify suitable practice priorities. These selections can help the system focus on areas where the candidate needs further improvement. The effectiveness of this approach depends on its implementation, problem formulation, and experimental evaluation. After each interview, the platform provides feedback to help students understand their performance and plan their next steps. The report can identify concepts that require revision, coding topics that need additional practice, project-related questions that were answered incompletely, and communication habits that may be improved. The system can also recommend relevant learning resources based on identified skill gaps. By reviewing reports from multiple sessions, students can track their progress and adjust their preparation according to their needs. This creates a continuous learning process in which students practice, receive feedback, and work on their weaknesses before attending actual interviews.

The main objective of the Quantum-Assisted AI Interview Intelligence and Placement Readiness Platform is to make interview preparation more structured, accessible, and personalized. By combining resume-based question generation, adaptive technical and HR interviews, voice interaction, coding practice, performance evaluation, and quantum-assisted optimization, the platform aims to address important gaps in conventional placement preparation. It provides students with an additional opportunity to practise independently, improve their technical and communication skills, and understand their readiness for recruitment interviews. Although the platform cannot guarantee placement success or replace human interviewers, it can serve as a useful preparation tool that supports continuous improvement and helps students approach interviews with better preparation and confidence.

2. RELATED WORK:

Fifteen studies related to AI-based interview preparation, resume analysis, adaptive question generation, speech recognition, coding assessment, computer vision, and quantum-assisted approaches were reviewed. These studies can be broadly classified into four groups.

AI-based interview preparation and resume analysis systems. Shree et al. [1] present an AI-driven mock interview platform that integrates resume analysis with personalized question generation and spoken-answer evaluation. Role-focused interview systems [2] use candidate resumes and job descriptions to generate relevant questions and identify skill gaps. NLP-based adaptive learning approaches [3] focus on providing immediate feedback, adjusting question difficulty, and evaluating candidate responses. Multi-agent LLM approaches [4][7] explore adaptive follow-up questioning and role-based interview interactions. These studies demonstrate the importance of personalized interview preparation and automated feedback. However, challenges such as inconsistent answer evaluation, dependency on external language models, privacy concerns, and limited real-world validation remain important considerations.

Speech recognition and multimodal interview assessment. Studies combining LLMs, Whisper, and computer vision [5][6][8] explore voice-based interview interaction and multimodal candidate assessment. These approaches use speech recognition to process spoken responses and visual information to support interview evaluation. Conversational AI systems integrating voice and emotion analysis [11][12] further investigate real-time feedback, speech clarity, and behavioural indicators. Such methods provide a foundation for developing natural voice-based interview environments. However, speech recognition errors, environmental noise, variations in speaking styles, visual accuracy, and privacy-related concerns can affect the reliability of automated assessment. These studies motivate the integration of Whisper for speech-to-text conversion and MediaPipe for facial landmark detection in QAIP.

Adaptive question generation, coding assessment, and placement evaluation. Resume-based question generation approaches using NLP and transformer models [10] focus on generating personalized questions according to candidate profiles. Resume classification and ranking methods [9] investigate candidate information extraction and evaluation. Synthetic coding-data generation and fine-tuning approaches [13] focus on improving coding-related model performance and benchmark evaluation. Recent AI-based interview platforms [14][15] combine resume analysis, adaptive questioning,

computer vision, and multimodal assessment to provide a broader evaluation of candidates. These studies demonstrate the usefulness of integrating multiple assessment techniques. However, several approaches have limitations related to dataset size, computational requirements, question relevance, coding evaluation, and generalization to different interview scenarios. These findings motivate QAIP to combine resume-based question generation, technical and HR interviews, coding practice, project-based assessment, and personalized performance reports.

Quantum computing and optimization-based approaches. Quantum-assisted optimization provides an alternative approach for solving complex selection and planning problems. The proposed QAIP explores the Quantum Approximate Optimization Algorithm (QAOA) for selecting relevant interview follow-up questions and prioritizing preparation activities. The question-selection process can consider candidate skill gaps, previous responses, question difficulty, topic coverage, and available preparation time. By formulating the selection problem as a Quadratic Unconstrained Binary Optimization (QUBO) problem, QAOA can be explored for identifying suitable combinations of questions. However, practical application depends on the quality of the optimization formulation, quantum circuit execution, hardware limitations, and comparison with classical approaches. This motivates the exploration of QAOA as a quantum-assisted component in QAIP.

Based on the reviewed studies, the proposed Quantum-Assisted AI Interview Intelligence and Placement Readiness Platform aims to integrate resume-based personalization, LLaMA 3-based question generation and answer evaluation, Whisper-based speech recognition, Media Pipe-based visual indicator analysis, coding assessment, and QAOA-based adaptive question selection into a unified interview preparation system. Unlike approaches that focus mainly on individual interview, speech, resume, or coding assessment components, QAIP brings these functionalities together to provide students with personalized interview practice, structured performance feedback, and preparation guidance.

Table 1. Summary of the Reviewed Literature

Ref.	Year	System / Focus	Key Strength	Limitation
[1]	2026	SBERT + LLaMA 3 + Whisper + ML models	Integrates resume analysis, adaptive questions, speech, and evaluation	Complex multimodal integration
[2]	2026	LLaMA 3 + MiniLM + Whisper + MediaPipe	Personalized role-based questions and skill-gap detection	Audio and visual accuracy affected by external factors
[3]	2026	NLP + Sentiment Analysis + Adaptive Learning	Immediate feedback and adaptive question difficulty	Tested mainly in controlled conditions
[4]	2026	Multi-agent LLM + Adaptive Follow-up	Context-aware and adaptive questioning	Limited language and evaluation conditions
[5]	2026	LLM + Digital Human + Vision-Language Model	Role-conditioned questions and multimodal assessment	Limited platform evaluation
[6]	2026	DeBERTa + Mistral + Whisper + WebRTC	Resume-grounded questions and real-time voice interviews	Small dataset and technical-answer validation challenges
[7]	2025	Multi-agent RAG-LLM	Modular, explainable, and role-adaptive evaluation	Bias, privacy, and external API dependency
[8]	2026	BERT + Wav2Vec 2.0 + Efficien Net	Combines resume, audio, and visual information	Synthetic data limits real-world generalization
[9]	2019	Heuristics + BERT	Multi-format resume parsing and candidate evaluation	Limited ground-truth ranking data
[10]	2025	NLP + FLAN-T5 + BERT/SBERT	Personalized interview questions and resume insights	Slow inference
[11]	2025	Conversational AI + Voice + Emotion Analysis	Real-time feedback and adaptive questions	Accuracy and privacy concerns
[12]	2024	CNN + Speech Recognition + NLP	Combines speech analysis and knowledge assessment	Emotion interpretation and privacy concerns

Ref.	Year	System / Focus	Key Strength	Limitation
[13]	2025	Synthetic Data Generation + SFT/RL	Large-scale coding dataset generation	Computational cost and data filtering
[14]	2025	Gemini + NLP + Computer Vision + Audio	Resume analysis, adaptive questions, and interview analytics	API and environmental dependency

2.1 Research Gap

The literature survey identifies five major gaps in existing AI-based interview preparation systems. The proposed QAIP platform addresses these gaps through the following design approaches.

Table 2. Identified Gaps and the Corresponding Design Response

Finding in literature	Research gap	Proposed response
Existing systems generate interview questions using resumes and job descriptions.	Limited personalization based on previous responses and continuously identified skill gaps.	LLaMA 3 for resume-based question generation, contextual follow-up questions, and answer evaluation.
Speech recognition is used to process spoken interview responses.	Speech transcription errors and difficulty evaluating spoken answers in a natural interview environment.	Whisper-based speech-to-text conversion for generating transcripts that can be evaluated by LLaMA 3.
Existing interview systems provide automated answer evaluation and feedback.	Inconsistent evaluation and limited identification of specific technical knowledge gaps.	LLaMA 3 with defined evaluation criteria such as correctness, relevance, completeness, and expected concepts.
Computer vision and multimodal approaches are used for interview assessment.	Limited integration of visual indicators with technical, communication, and coding performance.	MediaPipe-based facial landmark detection and supplementary visual indicators within the interview assessment report.
Existing preparation platforms often provide separate coding practice and interview evaluation features.	Lack of a unified environment for technical interviews, HR interviews, project discussions, coding practice, and personalized preparation.	Integrated interview platform with coding support through Monaco Editor and Judge0, structured assessment reports, and personalized preparation roadmaps.
Quantum optimization is explored for complex selection and planning problems.	Limited exploration of quantum-assisted optimization for personalized interview question selection and preparation priorities.	QAOA-based question selection formulated as a QUBO optimization problem, with comparison against a classical baseline.

Overall Research Gap:

Existing studies demonstrate progress in resume analysis, AI-based question generation, speech recognition, coding evaluation, and multimodal interview assessment. However, there is still a need for a unified platform that combines personalized technical and HR interview practice, spoken-answer evaluation, coding assessment, visual indicators, and structured preparation guidance. QAIP aims to address this gap by integrating these components and exploring QAOA for adaptive question selection and preparation planning.

3. PROPOSED SYSTEM ARCHITECTURE

3.1 Overall Architecture

The proposed Quantum-Assisted AI Interview Intelligence and Placement Readiness Platform (QAIP) follows a modular architecture designed to provide personalized interview preparation for students. The student interacts with the system through a web-based user interface, where they can upload their resume, select a target job role, and participate in technical, HR, and project-based mock interviews.

The uploaded resume is processed to extract relevant information, including educational qualifications, technical skills, projects, and experience. Based on this information and the selected job role, LLaMA 3 generates personalized interview questions and evaluates the candidate's responses using criteria such as correctness, relevance, completeness, and conceptual understanding.

For voice-based interviews, the candidate's spoken responses are captured and converted into text using OpenAI Whisper. The generated transcript is passed to LLaMA 3 for answer evaluation and feedback generation. MediaPipe processes webcam frames to detect facial landmarks and calculate supported visual indicators, which can be included as supplementary information in the interview assessment.

The platform also provides an integrated coding interview environment using Monaco Editor, allowing students to write and execute programming solutions through the Judge0 code execution service. Coding performance can be evaluated using execution results and test cases.

The quantum-assisted component uses the Quantum Approximate Optimization Algorithm (QAOA) to explore the selection of relevant follow-up questions and preparation priorities. The question-selection problem can be formulated as a Quadratic Unconstrained Binary Optimization (QUBO) problem by considering skill gaps, question relevance, difficulty level, topic coverage, and available preparation time.

Finally, the platform combines the available assessment results, including technical knowledge, coding performance, project understanding, communication-related indicators, and supported visual measurements, to generate a structured interview assessment report. Based on the identified weaknesses, the system provides a personalized preparation roadmap containing recommended topics, learning resources, and coding challenges. This helps students track their progress and improve their placement readiness.

3.2 User Roles

Role	**Responsibilities**
Student / Candidate	Registers and logs in to the platform, uploads a resume, selects a target job role, participates in technical and HR mock interviews, provides spoken or text-based answers, solves coding questions, reviews assessment reports, and follows the personalized preparation roadmap.
Administrator	Manages platform configurations, maintains relevant system information, monitors platform operations, and manages available resources and user-related information, where supported by the implementation.
AI Interview Module	Uses LLaMA 3 to generate resume-based technical, HR, and project-related questions, evaluate candidate responses, generate adaptive follow-up questions, identify skill gaps, and provide personalized feedback.
Speech and Visual Processing Module	Uses Whisper to convert spoken responses into text and MediaPipe to detect facial landmarks and calculate supported visual indicators during mock interviews.
Quantum Optimization Module	Uses QAOA to formulate and explore adaptive question selection and preparation prioritization based on candidate performance, skill gaps, question relevance, and available preparation time.
Coding Assessment Module	Provides a programming interface using Monaco Editor and supports code execution through Judge0. It evaluates coding solutions using execution results and available test cases.
Assessment and Roadmap Module	Combines available interview assessment information, generates structured performance reports, identifies improvement areas, and recommends personalized learning activities and coding challenges.

3.3 Technology Stack

Layer	**Technology**	**Purpose**
Front End	Web-based User Interface	Provides an interactive interface for resume uploads, mock interviews, coding practice, performance reports, and preparation roadmaps.

Layer	Technology	Purpose
Programming Language	Python	Implements backend logic, AI model integration, speech processing, optimization, and interview assessment operations.
Large Language Model	LLaMA 3	Generates personalized interview questions, evaluates candidate responses, identifies knowledge gaps, and provides feedback.
Speech Recognition	OpenAI Whisper	Converts the candidate's spoken interview responses into text for further evaluation.
Visual Processing	MediaPipe	Detects facial landmarks and supports the calculation of selected visual indicators from webcam frames.
Quantum Computing	QAOA (Quantum Approximate Optimization Algorithm)	Explores optimization-based selection of relevant follow-up questions and preparation priorities.
Quantum Framework	Qiskit	Supports the formulation and implementation of quantum optimization circuits for the QAOA component.
Coding Editor	Monaco Editor	Provides an integrated programming environment for writing and editing coding interview solutions.
Code Execution	Judge0	Executes candidate-submitted programs and provides execution results for coding assessment.
Resume Processing	Resume Parsing / Information Extraction	Extracts candidate details, educational qualifications, skills, projects, and experience for personalized interview generation.
Assessment and Feedback	LLaMA 3-Based Evaluation	Evaluates interview responses using correctness, relevance, completeness, and conceptual understanding criteria.
Database / Data Storage	Platform Data Storage	Maintains relevant candidate information, resume details, interview sessions, responses, assessment results, and preparation progress.
Reporting	Assessment Report Generation	Presents interview scores, strengths, weaknesses, feedback, and recommendations for improvement.
Learning Support	Personalized Preparation Roadmap	Organizes recommended learning topics, study activities, resources, and coding challenges based on identified skill gaps.

4. METHODOLOGY

4.1 AI-Based Interview Preparation Lifecycle

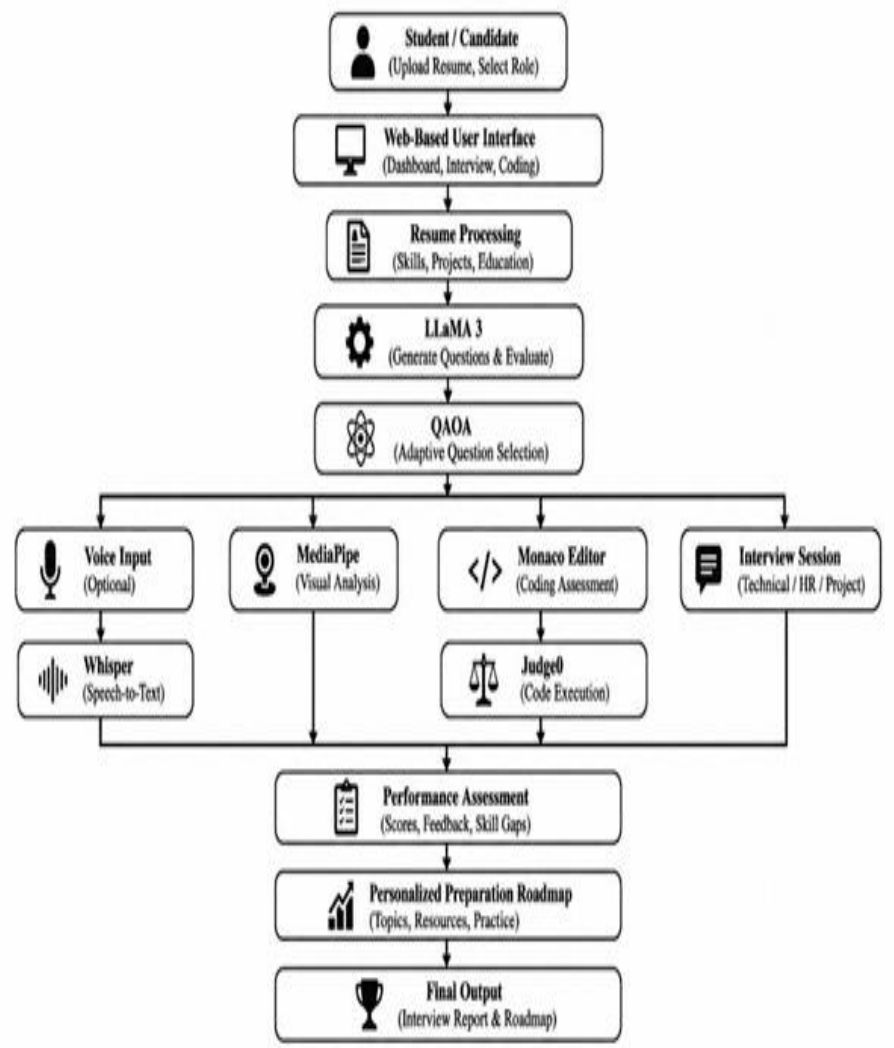


Fig. 1. Overall Architecture and Methodology of QAIP

Fig. 1 illustrates the end-to-end workflow of the proposed Quantum-Assisted AI Interview Intelligence and Placement Readiness Platform (QAIP). The major steps are as follows:

1. **Candidate Profile Input:** The candidate accesses the platform through the web interface and provides the required details, including their resume, technical skills, academic projects, educational background, and target job role.
2. **Resume Processing:** The uploaded resume is processed to identify relevant information such as technical skills, projects, qualifications, and areas of experience. The extracted information is used to personalize the interview process.
3. **Question Generation:** LLaMA 3 uses the candidate's profile, target role, and selected interview category to generate relevant technical, HR, and project-based interview questions.
4. **Adaptive Question Selection:** The QAOA-based optimization component formulates the question-selection process as a combinatorial optimization problem. Candidate questions are represented using binary decision variables, and a QUBO formulation is used to identify suitable question combinations based on relevance, difficulty, topic coverage, and available time.
5. **Interview Interaction:** The candidate answers the generated questions through the interview interface. The platform supports text-based and voice-based interaction, depending on the selected interview mode.
6. **Speech-to-Text Conversion:** For voice-based interviews, OpenAI Whisper processes the recorded audio and converts the candidate's spoken answers into textual transcripts. These transcripts are passed to LLaMA 3 for further analysis.

7. **Answer Evaluation:** LLaMA 3 evaluates the candidate's responses using defined assessment criteria such as technical correctness, relevance, completeness, and conceptual understanding. The system identifies strengths and knowledge gaps and generates feedback.
8. **Visual Indicator Analysis:** MediaPipe processes webcam frames and detects facial landmarks. Supported measurements, such as face presence or head orientation, can be included as supplementary visual information when implemented.
9. **Coding Assessment:** The candidate can solve programming questions using the integrated Monaco Editor. The submitted code is executed through the Judge0 code execution service, allowing practical coding performance to be considered during assessment.
10. **Performance Report Generation:** The platform combines the available interview responses, evaluation scores, coding results, communication-related measures, and supported visual indicators to prepare a structured assessment report.
11. **Personalized Preparation Roadmap:** Based on the identified knowledge gaps and target job role, the platform provides preparation recommendations, priority topics, coding challenges, and learning activities to help candidates improve their placement readiness.

4.2 Role-Based Access and Module Responsibilities

The proposed QAIP platform follows a component-based architecture in which each module performs a specific responsibility during the interview preparation process. The candidate interacts with the platform, while the AI-based modules process the candidate's information, responses, and performance.

The proposed system follows these principles:

- **Candidate Interaction:** The candidate uploads a resume, selects an interview category, answers questions, and accesses the assessment report.
- **Resume Processing:** Relevant candidate information is extracted and used to generate personalized interview questions.
- **AI-Based Interview Processing:** LLaMA 3 generates contextual questions, evaluates responses, identifies knowledge gaps, and provides feedback.
- **Speech Recognition:** Whisper converts recorded spoken responses into text for further evaluation.
- **Quantum Optimization:** QAOA formulates adaptive question selection as an optimization problem and explores suitable question combinations.
- **Visual Processing:** MediaPipe detects facial landmarks and supports selected visual measurements when implemented.
- **Coding Assessment:** Monaco Editor provides the coding interface, while Judge0 executes submitted programs.
- **Performance Assessment:** The assessment module consolidates available results and generates personalized preparation recommendations.

Table 3. Role–Module Responsibility Matrix

Role / Component	Provide Input	Generate Questions	Process Responses	Evaluate Performance	Generate Report	Provide Roadmap
Student / Candidate	Yes	No	Yes	No	View report	View roadmap
Resume Processing Module	Resume details	No	No	No	No	No
LLaMA 3 Module	No	Yes	Yes	Yes	Assessment data	Identify skill gaps
Whisper Module	Audio input	No	Speech-to-text	No	Transcript	No
QAOA Module	Candidate and question data	Select questions	No	Optimization output	No	Prioritize activities
MediaPipe Module	Webcam frames	No	Visual processing	Visual indicators	Visual data	No
Coding Assessment Module	Source code	No	Code execution	Coding results	Coding data	Coding practice
Assessment and Roadmap Module	Assessment data	No	Consolidate results	Yes	Yes	Yes

4.3 AI-Based Interview Workflow

The AI-based interview process is the core functionality of the proposed QAIP platform. Initially, the candidate provides their resume and selects the required interview category or target job role. The system processes the candidate's profile and extracts relevant information, including technical skills, academic projects, and educational details.

LLaMA 3 uses this information to generate personalized technical, HR, and project-related questions. During the interview, the candidate submits answers through the available interaction interface. If voice interaction is selected, the recorded audio is passed to OpenAI Whisper, which converts the spoken response into text.

The resulting transcript is supplied to LLaMA 3 for evaluation. The model checks the response based on technical correctness, relevance, completeness, and the presence of expected concepts. Based on the evaluation, the system generates feedback and identifies areas that require improvement. Previous responses and identified skill gaps can also be used to support contextual follow-up questions.

The QAOA component can support the selection of suitable follow-up questions by considering question relevance, difficulty, topic coverage, and available time. The selected questions are then passed to the AI interview module for the next stage of the interview.

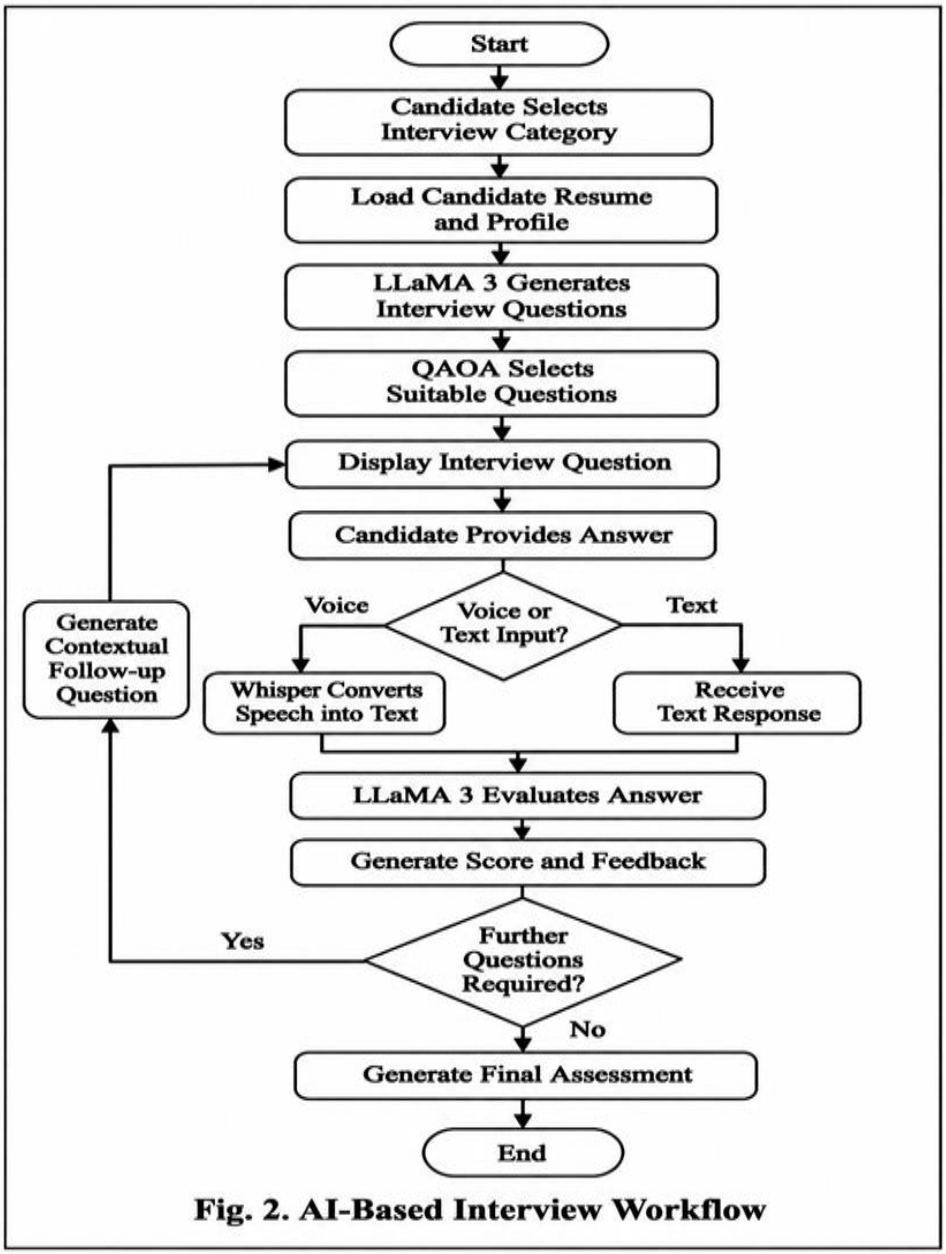


Fig. 2. AI-Based Interview Workflow of QAIP

Table 4. Interview Operations and Processing Conditions

Operation	Processing Chain	Condition
Candidate Profile	Candidate → Resume Upload	Resume and relevant profile information are provided.
Resume Processing	Resume → Information Extraction	Skills, projects, and educational details are identified.
Question Generation	Candidate Profile → LLaMA 3	Questions are generated according to the candidate's profile and target role.
Question Selection	Candidate Questions → QAOA	Suitable questions are selected based on the defined optimization objective and constraints.
Voice Input	Candidate → Microphone	Spoken interview answers are recorded.
Speech Recognition	Audio → Whisper → Text	Recorded answers are converted into textual transcripts.
Answer Evaluation	Response → LLaMA 3	Answers are evaluated using defined assessment criteria.
Visual Processing	Webcam Frames → MediaPipe	Facial landmarks and supported visual indicators are processed.
Coding Assessment	Monaco Editor → Judge0	Submitted programs are executed and coding results are obtained.
Report Generation	Assessment Data → Report Module	Available evaluation results are consolidated into a structured report.
Roadmap Generation	Skill Gaps → Preparation Module	Priority topics and learning activities are recommended.

The AI interview, speech recognition, question optimization, visual processing, and coding assessment modules work together as an integrated preparation workflow. LLaMA 3 handles question generation and answer evaluation, Whisper processes spoken responses, QAOA supports adaptive question selection, and MediaPipe provides supplementary visual measurements. The coding environment enables candidates to practice programming questions. The outputs from these modules are consolidated to support performance reporting and personalized preparation guidance.

4.4 Quantum-Assisted Adaptive Question Selection

The proposed system uses the Quantum Approximate Optimization Algorithm (QAOA) to formulate adaptive question selection as a combinatorial optimization problem.

During an interview, candidates may demonstrate different levels of understanding across technical subjects. For example, a candidate may perform well in Python but have difficulty answering questions related to database management or operating systems. Therefore, the platform aims to prioritize questions that address the candidate's knowledge gaps rather than repeatedly selecting questions from already mastered topics.

Each candidate question is represented using a binary decision variable. A value of 1 indicates that the question is selected, while a value of 0 indicates that it is not selected. The optimization objective considers factors such as:

- Relevance to the candidate's target job role.
- Difficulty level of the question.
- Coverage of important technical topics.
- Identified knowledge gaps from previous answers.
- Available interview or preparation time.
- Desired number of questions.
- Avoidance of unnecessary question repetition.

The objective function is converted into a Quadratic Unconstrained Binary Optimization (QUBO) formulation. The corresponding cost Hamiltonian is used to construct the QAOA circuit.

The major steps involved in the QAOA methodology are:

1. Identify the candidate's knowledge gaps and available questions.
2. Assign binary decision variables to the candidate questions.
3. Define the optimization objective and required constraints.
4. Convert the objective into a QUBO formulation.
5. Construct the corresponding quantum circuit.
6. Initialize the circuit using a superposition of possible question combinations.
7. Apply QAOA cost and mixing operations using adjustable parameters.
8. Measure the quantum circuit to obtain candidate solutions.
9. Use a classical optimizer to update the circuit parameters.
10. Evaluate the resulting solutions and select a suitable question combination.
11. Pass the selected questions to the AI interview module.

The effectiveness of QAOA should be evaluated by executing the optimization circuit and comparing its results with a suitable classical or rule-based baseline. Quantum optimization should not be considered superior unless experimental results demonstrate an improvement.

4.5 Digital Assessment and Personalized Preparation Management

The proposed platform supports structured performance assessment and preparation guidance by combining the available results from different modules.

The assessment process includes the following functionalities:

- **Technical Answer Evaluation:** LLaMA 3 evaluates the candidate's responses based on correctness, relevance, completeness, and conceptual understanding.
- **Communication Assessment:** Available speech and response information can be used to provide communication-related feedback.
- **Coding Performance:** The integrated Monaco Editor and Judge0 environment supports programming practice and code execution.
- **Visual Indicator Analysis:** MediaPipe provides facial landmark information and selected visual measurements when implemented.
- **Performance Consolidation:** The assessment module combines the available results to identify strengths and areas requiring improvement.
- **Personalized Roadmap:** The platform recommends priority topics, daily preparation activities, coding challenges, and learning resources based on identified skill gaps.
- **Progress Tracking:** The student dashboard provides available interview-session information, completed interviews, average scores, and recent performance details.

The generated assessment report helps candidates understand their performance across different interview activities. The personalized roadmap provides a structured approach to improving technical knowledge, communication, project understanding, and coding skills before attending actual placement interviews.

4.6 Security, Reliability, and Responsible Processing

Security and reliability are important considerations in the proposed QAIP platform because it processes candidate resumes, interview responses, audio recordings, webcam frames, and performance information.

The proposed system considers the following principles:

- **Candidate Data Handling:** Resume details and interview responses should be processed only for the intended interview preparation and assessment activities.
- **Controlled Data Access:** Access to candidate information and assessment results should be restricted according to the platform's implemented access controls.

- **Speech Recognition Reliability:** Whisper transcripts should be checked for errors because background noise, pronunciation, accents, and technical terminology can affect transcription quality.
- **Answer Evaluation Reliability:** LLaMA 3 evaluations should follow a defined scoring rubric and should be validated against human-reviewed answers to reduce inconsistent or unsupported feedback.
- **Optimization Validation:** QAOA results should be compared with classical baseline methods to assess solution quality and constraint satisfaction.
- **Visual Data Reliability:** MediaPipe outputs should be treated as supplementary measurements. Facial landmarks alone cannot establish a candidate's confidence, honesty, or technical ability.
- **Coding Validation:** Submitted programs should be evaluated through the configured code execution environment and appropriate test cases.
- **Fair Assessment:** Automated feedback should focus on measurable interview performance and should not be treated as an independent decision about a candidate's recruitment suitability.

The reliability of the final assessment depends on the correct functioning of individual modules, suitable evaluation criteria, and systematic testing of the complete interview workflow.

5. IMPLEMENTATION AND EVALUATION PLAN

5.1 Implementation Status

The QAIP project is carried out in stages, including literature survey, requirement analysis, system planning, architecture design, module development, integration, testing, evaluation, and documentation. The implementation involves developing a web-based interview preparation platform that supports resume-based personalization, AI-generated interview questions, voice-based interaction, coding assessment, and personalized preparation guidance.

The resume processing module extracts relevant candidate information, including educational qualifications, technical skills, academic projects, and experience. LLaMA 3 is integrated to generate personalized technical, HR, and project-based interview questions, evaluate candidate responses, generate contextual follow-up questions, and provide performance feedback.

The speech processing module integrates OpenAI Whisper to convert spoken interview responses into textual transcripts for further evaluation. MediaPipe is used for facial landmark detection and visual indicator processing during interview sessions. The coding assessment module integrates Monaco Editor for writing programming solutions and Judge0 for executing submitted code and obtaining execution results.

The quantum-assisted optimization component explores the use of the Quantum Approximate Optimization Algorithm (QAOA) for adaptive interview question selection and preparation prioritization. The question-selection problem is formulated using Quadratic Unconstrained Binary Optimization (QUBO), considering factors such as question relevance, difficulty, topic coverage, candidate knowledge gaps, and available preparation time. Qiskit supports the formulation and execution of the quantum optimization component.

The assessment module combines available interview evaluation results, coding performance, and supported visual indicators to generate structured performance reports. The personalized preparation module uses identified knowledge gaps to recommend priority topics, learning resources, and coding challenges. The student dashboard provides access to interview sessions, assessment results, and preparation progress.

System integration, functional testing, performance evaluation, validation of the optimization component, and project documentation are carried out as subsequent stages of the project.

5.2 Evaluation Protocol

The proposed QAIP platform will be evaluated using sample candidate resumes, technical and HR interview questions, spoken responses, coding problems, and candidate performance data. The evaluation will focus on the effectiveness of resume processing, question generation, speech recognition, answer evaluation, coding assessment, visual processing, and quantum-assisted question selection.

The system will be assessed using suitable quantitative and qualitative evaluation metrics. The QAOA-based optimization component will also be compared with a classical optimization or baseline question-selection approach to examine solution quality and computational performance.

The evaluation will consider the accuracy of candidate information extraction, relevance of generated interview questions, agreement between automated and human-reviewed answer evaluations, speech transcription quality, coding execution correctness, optimization performance, and overall system usability. No additional performance figures are claimed in this section; evaluation results should be reported after completing the corresponding experiments.

Table 5. Evaluation Metrics

Metric	Definition	Baseline for Comparison
Resume Information Extraction Accuracy	Measures the correctness of extracted candidate information, including skills, education, projects, and experience.	Manually verified resume information
Interview Question Relevance	Evaluates whether generated questions are relevant to the candidate's resume, skills, and selected job role.	Human-reviewed interview questions
Question Generation Quality	Measures the contextual relevance, clarity, diversity, and appropriateness of generated interview questions.	Expert-reviewed question set
Answer Evaluation Accuracy	Measures how accurately LLaMA 3 evaluates candidate responses based on correctness, relevance, completeness, and expected concepts.	Human-evaluated answers
Speech Recognition Accuracy	Measures the percentage of spoken interview content correctly converted into text by Whisper.	Manually transcribed speech
Word Error Rate (WER)	Measures transcription errors, including substitutions, deletions, and insertions in the recognized text.	Actual spoken transcript
Coding Assessment Accuracy	Evaluates the correctness of submitted programming solutions using test cases and execution results.	Expected outputs and verified test cases
Visual Processing Accuracy	Evaluates the correctness of supported facial landmark detection and visual measurements using MediaPipe.	Manually verified visual observations or annotated reference data
QAOA Optimization Performance	Evaluates the quality of selected question combinations based on the defined QUBO objective and constraints.	Classical optimization or baseline question selection
QAOA Execution Time	Measures the time required to execute the optimization process and obtain candidate solutions.	Classical optimization execution time
Performance Assessment Consistency	Evaluates the consistency of generated assessment scores across repeated or equivalent evaluation conditions.	Human-reviewed assessment results
System Response Time	Measures the time required for question generation, answer evaluation, speech processing, and other major system operations.	Recorded execution time under the same conditions
Roadmap Recommendation Relevance	Evaluates whether recommended topics and coding challenges address the candidate's identified knowledge gaps.	Expert-reviewed preparation recommendations
Usability	Evaluates the ease of using the platform for resume uploads, interview participation, coding practice, and performance report access.	User feedback and usability questionnaire

5.3 Results

The QAIP application interface was developed to support resume-based interview preparation, AI-generated questions, voice-based interview interaction, coding practice, performance assessment, and personalized preparation planning. The implemented interface provides access to the major functionalities and user interactions available in the platform.

The results presented in this section focus on the functional modules, platform workflow, assessment outputs, and available performance comparisons.

Student Dashboard Module: The student dashboard provides access to interview preparation activities, available interview sessions, assessment information, and preparation progress. It acts as the main navigation interface for accessing the platform's features.

Resume Processing and Interview Preparation Module: The resume-based preparation functionality allows candidates to provide their resume information and select a target job role. The extracted candidate details, including technical skills, projects, and educational qualifications, are used to personalize interview questions and preparation activities.

AI-Based Mock Interview Module: The mock interview functionality supports technical, HR, and project-based interview practice. LLaMA 3 generates relevant questions and evaluates candidate responses. The module also supports contextual follow-up questions based on previous answers and identified knowledge gaps.

Voice-Based Interview Module: The voice interview functionality allows candidates to provide spoken responses during mock interviews. OpenAI Whisper converts the recorded audio into textual transcripts, which are processed by LLaMA 3 for answer evaluation and feedback generation.

Visual Assessment Module: The visual processing component uses MediaPipe to detect facial landmarks from webcam frames and calculate supported visual indicators. The processed information can be used as supplementary input in the interview assessment process.

Coding Assessment Module: The coding functionality integrates Monaco Editor to provide an environment for writing and editing programming solutions. Judge0 executes the submitted code and provides execution results for evaluating coding performance.

Interview Assessment Report: The assessment report presents the candidate's available performance information, including technical knowledge, communication-related evaluation, problem-solving performance, coding results, and other supported assessment indicators. It helps candidates understand their strengths and identify areas requiring improvement.

Personalized Preparation Roadmap: The preparation roadmap provides recommended learning topics, priority areas, coding challenges, and learning resources based on the candidate's assessment results and identified skill gaps. It helps students organize their preparation activities and monitor improvement.

Performance Comparison: The report includes a comparison between the existing LLM-based approach and the proposed QAOA-based approach using evaluation metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. These metrics are used to examine the reported evaluation performance of the approaches. The comparison should be interpreted according to the experimental setup and dataset used in the evaluation.

The implemented modules collectively provide an integrated environment for interview preparation, automated feedback, coding practice, and placement readiness improvement. The results demonstrate the functional workflow of the proposed QAIP platform and its approach to combining AI-based .assessment with quantum-assisted optimization.

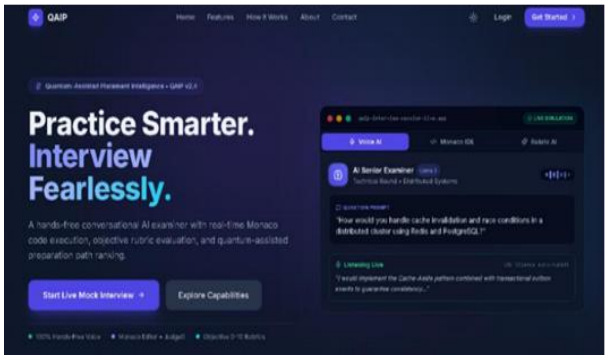


Fig 5.1: QAIP interface



Fig 5.2: Interview assessment report

6. DISCUSSION

Expected Benefits. The proposed QAIP platform is designed to improve students' placement preparation by providing personalized and interactive mock interview experiences. Resume-based question generation using LLaMA 3 helps generate relevant technical, HR, and project-based questions according to the candidate's skills, educational background, projects, and target job role. Adaptive follow-up questions help examine the candidate's conceptual understanding and identify knowledge gaps. Whisper enables voice-based interview interaction by converting spoken responses into text for further evaluation, while MediaPipe supports facial landmark detection and supplementary visual indicator analysis. The integration of Monaco Editor and Judge0 provides a coding environment where students can practise programming questions and execute their solutions. Furthermore, QAOA explores optimization-based selection of relevant interview questions and preparation priorities based on individual performance, skill gaps, and available preparation time. The platform also generates structured performance reports and personalized preparation roadmaps, helping students identify weaknesses, track progress, and focus on areas requiring improvement. The actual effectiveness of these components will be determined through systematic evaluation using interview sessions, reference transcripts, human-graded answers, coding test cases, and comparison with classical question-selection approaches**.**

Limitations. The performance of LLaMA 3-based question generation and answer evaluation may vary depending on prompt quality, candidate input, response context, and the consistency of evaluation criteria. Whisper transcription accuracy may be affected by background noise, unclear pronunciation,

accents, and technical terminology. MediaPipe-based visual analysis depends on webcam quality, lighting conditions, camera positioning, and facial visibility. Facial landmarks and visual measurements alone cannot reliably determine a candidate's confidence, personality, or overall interview ability. The coding assessment module also depends on the correctness of test cases, supported programming languages, and the reliability of the code execution environment. Additionally, QAOA implementation involves challenges related to QUBO formulation, quantum circuit complexity, hardware limitations, and scalability. Its effectiveness must be validated by comparing its optimization results with suitable classical baseline methods. The generated assessment scores and feedback may also contain inconsistencies and should be validated against human-reviewed evaluations. Furthermore, the platform requires appropriate handling of sensitive candidate information, including resumes, audio recordings, webcam data, and interview results. Practical testing with diverse candidates and real interview scenarios is necessary to establish the reliability, scalability, and effectiveness of the proposed system.

7. CONCLUSION AND FUTURE SCOPE

This paper presented the Quantum-Assisted AI Interview Intelligence and Placement Readiness Platform (QAIP), an AI-driven interview preparation system integrated with quantum optimization techniques to support students preparing for campus placement interviews. The proposed system combines resume-based question generation, LLaMA 3-based answer evaluation, Whisper speech recognition, and MediaPipe-based visual indicator analysis to provide personalized technical, HR, and project-based interview experiences. The integration of Monaco Editor and Judge0 provides an interactive coding environment for programming practice and code execution. Furthermore, the Quantum Approximate Optimization Algorithm (QAOA) is incorporated to explore adaptive follow-up question selection and personalized preparation planning based on candidate performance, identified skill gaps, target job roles, and available preparation time. The platform also generates structured interview assessment reports and personalized preparation roadmaps to help students identify their weaknesses, monitor progress, and improve their placement readiness. By integrating these technologies, QAIP aims to provide a unified and personalized environment for effective interview preparation.

Future Scope:

Future Future enhancements to QAIP will focus on improving interview evaluation accuracy, personalization, quantum optimization, speech processing, and practical deployment. The following developments can be considered:

· **Advanced Quantum Optimization:** Explore improved QAOA formulations for selecting relevant follow-up questions and prioritizing preparation activities. Test the optimization model on quantum hardware and compare its performance with classical optimization methods to determine its practical effectiveness.

· **Improved Personalization:** Extend the platform to maintain candidate preparation history across multiple interview sessions. Analyze previous scores, repeated mistakes, completed topics, and learning progress to recommend suitable preparation activities and dynamically adjust question difficulty.

· **Expanded Question Bank and Domain Coverage:** Increase the collection of interview questions covering Data Structures and Algorithms, Database Management Systems, Operating Systems, Computer Networks, Object-Oriented Programming, System Design, and emerging technologies. Introduce additional domain-specific question sets for different job roles.

· **Enhanced Answer Evaluation:** Improve LLaMA 3-based evaluation using stronger assessment rubrics and domain-specific reference answers. Incorporate human-evaluated datasets to measure agreement between AI-generated scores and expert assessments, improving the consistency and reliability of feedback.

· **Multilingual Speech Support:** Extend the Whisper-based speech processing component to support additional languages and mixed-language responses. Improve recognition of Indian English accents, technical terminology, background noise, and different speaking speeds to make voice-based interviews more accessible.

· **Advanced Visual and Communication Analysis:** Enhance MediaPipe-based visual processing to support additional measurable interview indicators. Improve communication feedback using speaking rate, filler-word frequency, and other relevant speech characteristics while ensuring that visual indicators remain supplementary to technical assessment.

· **Enhanced Coding Assessment:** Expand the coding environment to support additional programming languages, larger coding question banks, advanced test cases, and more comprehensive evaluation of code correctness and problem-solving approaches.

· **Real-World Deployment and Evaluation:** Deploy and evaluate the platform with students across different academic backgrounds and target job roles. Conduct practical testing using recorded interview sessions, human-graded answers, coding test cases, and classical optimization baselines to assess accuracy, reliability, usability, and scalability.

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