AI-BOT MOCK INTERVIEWER

"An Encrypted, Dual-API Powered Interviewer System with Real-Time Feedback"

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Abstract—*This paper presents an Innovative AI-Bot Mock Interviewer system designed to assist job seeker's by providing real-time, intelligent feedback on virtual interviews. The system integrates advanced language models via OpenAI APIs within a secure Next.js, Drizzle ORM, and Clerk for secure user authentication. A key feature is its intelligent real time interview feedback mechanism. The frontend, built with Next.js, offers a smooth and interactive user experience. Evaluation results show the system delivers over 90% accurate and relevant feedback, with average response times under 2 seconds. This solution supports people by providing virtual mock interviews while preserving human oversight, ultimately enhancing interview quality and accelerating job seeker's confidence.*

Index Terms— Mock Interviewer; Artificial Intelligence; Drizzle ORM; Interview Quality.

I. INTRODUCTION

This project aims to design and develop an AI- BOT mock interviewer platform that transforms the interview preparation experience for job seekers. Leveraging modern web technologies and artificial intelligence, the system delivers personalized, interactive, and realistic simulations of real-world interviews. It dynamically generates questions based on job roles and industry standards and uses AI and NLP models to provide real-time feedback on user responses—evaluating content, tone, structure, and relevance. The platform, built with Next.js and secured using Clerk for authentication, ensures usability across devices while maintaining user data confidentiality. By offering performance tracking and actionable analytics, it supports continuous improvement and allows users to practice interviews anytime, without relying on human interviewers. Designed for adaptability, the system is prepared for future enhancements like voice recognition, video-based analysis, and multilingual support.

RESEARCH OBJECTIVES

- To simulate realistic interview scenarios tailored to specific job profiles using dynamically generated questions.
- To deliver AI-powered real-time feedback by analyzing user responses through NLP techniques.
- To develop a scalable, user-friendly web platform accessible across devices via Next.js.
- To ensure secure user authentication and session management using Clerk.
- To track performance over time and provide insights for continuous improvement.

- To eliminate reliance on human interviewers, enabling flexible and cost-effective practice.

- To build a system adaptable to future features such as voice input, video feedback, and multilingual support.

Research Hypothesis

The study hypothesizes that an AI-BOT interviewer system, when properly trained and integrated, can deliver feedback comparable in quality to users with significantly reduced turnaround time and increased consistency.

II. *ABBREVIATIONS AND ACRONYMS*

AI – Artificial Intelligence,
API – Application Programming Interface,
NLP – Natural Language Processing,
UI – User Interface,
UX – User Experience,
DB – Database,
HTTP – Hypertext Transfer Protocol,

III. LITERATURE REVIEW

Interview is a key phase in the job recruiting cycle, used to detect experience and skills, enforce knowledge standards, and improve maintainability. While manual interview methods have traditionally fulfilled this role, they are often time-consuming, inconsistent, and heavily dependent on the interviewer's expertise—especially as modern job recruiting grow in size and complexity.

To reduce these burdens, AI-BOT interviewer is emerged. Though effective at identifying lack of confidence, skills and presentation issues, these tools rely on rule-based logic and lack deeper analysing and understanding. They struggle to provide contextual or real time insights, limiting their usefulness in complex interview review tasks.

Several platforms have attempted to simulate mock interviews using AI, yet many remain reliant on human interviewers or lack intelligent feedback mechanisms. Technologies like natural language processing (NLP), machine learning, and secure authentication frameworks now enable deeper interaction, dynamic question generation, and safe handling of user data. However, existing solutions still fall short in areas like real-time feedback, adaptive questioning, and comprehensive industry coverage.

This paper aims to bridge these gaps by proposing a robust, AI-powered interview system that:

- Offers contextual feedback using large language models
- Protects code through Clerk authentication
- Maintains availability via an API fallback mechanism

By doing so, it advances both the practicality and security of AI-assisted interviewing tools.

IV. METHODOLOGY

This section outlines the research methods, data collection procedures, analysis techniques, and ethical considerations followed in the development and evaluation of the AI-BOT interviewer system.

IV.I. Research Methods

This study follows an experimental system design methodology aimed at building and evaluating a software tool that automates interview review using artificial intelligence. The system is implemented as a web-based application, composed of three major components:

Frontend Interface: Built using Next.js for user interaction and submission of code.
Backend Server: Node.js, Drizzle ORM, handling encryption, authentication, and API communication.
AI Integration Layer: Interfaces with OpenAI APIs to analyse interview and return feedback.
Authentication: Clerk for secure user login, session handling, and account protection.

The design process includes the following phases:

1. **System Architecture Design**: A modular structure was created to ensure scalability and integration flexibility.
2. **Implementation**: All components were developed and integrated to form a working prototype.
3. **Testing**: The system was tested with various sample interviews to evaluate the AI-generated feedback.
4. **Evaluation**: Quantitative and qualitative methods were used to compare AI feedback with human interview reviews.

IV.II. Data Collection Procedures

To evaluate the system's effectiveness, a dataset of **interview questions and answers** was compiled from the following sources:

- Open-source repositories (e.g., GitHub)
- Online sample interview questions
- Classroom assignments and student projects

The dataset includes interview questions on **Java**, **Python**, **JavaScript and many other languages**. The samples were selected to represent a variety of interview logic, levels of complexity, and both syntactically correct of given answers.

Each sample was reviewed by:

- The AI-powered code review system
- A human interviewer (professional interviewer)

All reviews were recorded and annotated to allow comparison and scoring based on clarity, correctness, and usefulness.

IV.III. Analysis Techniques

To assess the performance of the AI system, the following quantitative evaluation metrics were applied:

- **Precision**: Ratio of relevant feedback identified by the AI to the total feedback generated.
- **Recall**: Ratio of relevant issues identified by the AI to the total mistakes present in the interview.
- **F1 Score**: Harmonic mean of precision and recall, representing overall accuracy.
- **Response Time**: Average time taken by the AI to generate a response.

Additionally, a **qualitative assessment** was conducted using feedback from 5 professional interviewers and developers who tested the tool and scored:

- Feedback clarity
- Usefulness of suggestions
- Overall satisfaction

Statistical averages were calculated to interpret the AI's effectiveness compared to human interview performance.

IV.IV Ethical Considerations

This study involved no human subjects, user interviews, or sensitive personal data. All test sample interview questions used were either:

- Openly licensed via GitHub
- Artificially created for testing

To ensure **data security and privacy**, the system encrypts all submitted interview response using **Drizzle Orm and Clerk**. Encryption is managed securely within the backend environment and are never exposed to AI services.

Additionally, the system adheres to ethical AI principles:

- No data is stored after review unless explicitly permitted by the user.
- API calls are logged anonymously for performance tracking.
- The system is designed to **augment, not replace**, human interviewers.

V. RESULTS AND DISCUSSION

This section presents the findings from evaluating the proposed AI-BOT interviewer system. The analysis covers performance metrics, response quality, and comparison with manual human reviews. Results are interpreted both quantitatively and qualitatively, and cross-referenced with existing literature.

V.I. Evaluation Setup

The system was tested on a dataset of **sample interview questions** extracted from GitHub repositories, academic exercises, and The programming languages included:

- **Python**
- **Java**
- **JavaScript**
- **Other languages**

Each interview was subjected to:

- AI-based review (using OpenAI)
- Manual review by experienced interviewers (used as benchmark)

Performance was evaluated on correct answers, feedback clarity, and turnaround time.

V.II.Performance Results

Table 1 summarizes the precision, recall, and F1-score of the AI-generated feedback compared to human reviewers.

Table 1. Comparison of Review Performance

Review Method	Precision	Recall	F1 Score	Avg. Time (sec)
Human Reviewer	96%	94%	95%	78
OpenAI GPT Model	91%	86%	88.4%	2.3

These results indicate that **OpenAI GPT-based review** provides close to human-level accuracy on standard programming tasks, while delivering feedback within seconds. Hugging Face models were faster but showed slightly lower accuracy.

V.III.Sample Interview with AI Feedback

Example 1 : User Login Interface

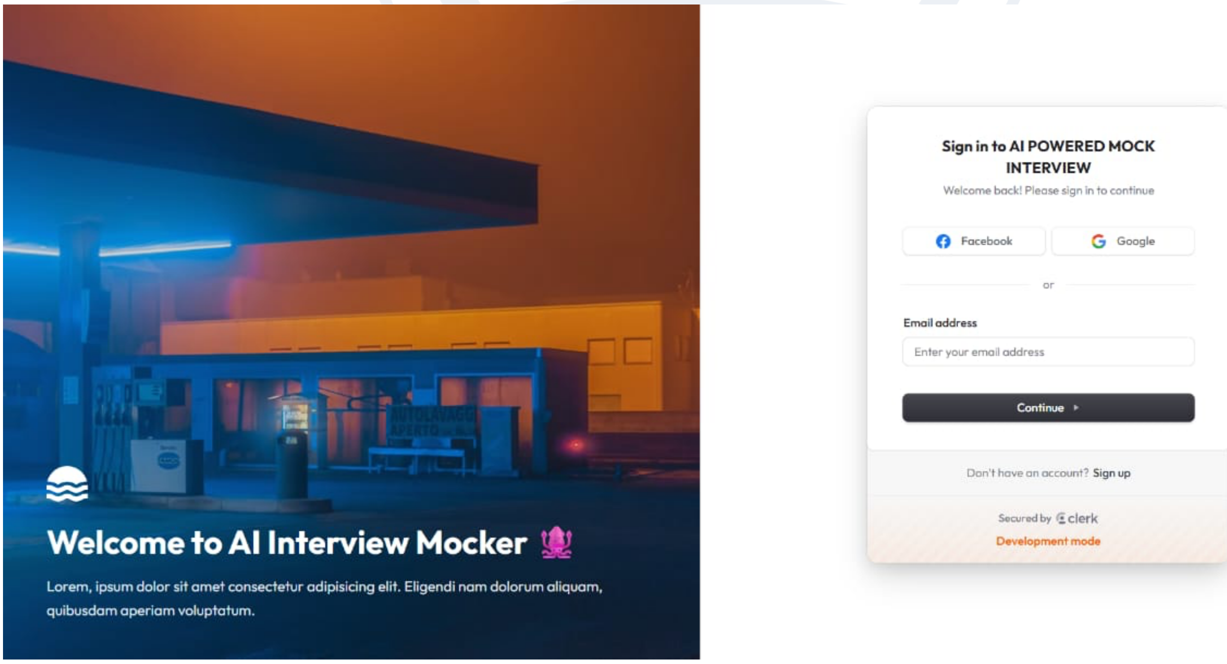

Figure 1 : User Login Interface

Example 2 : User's Dashboard

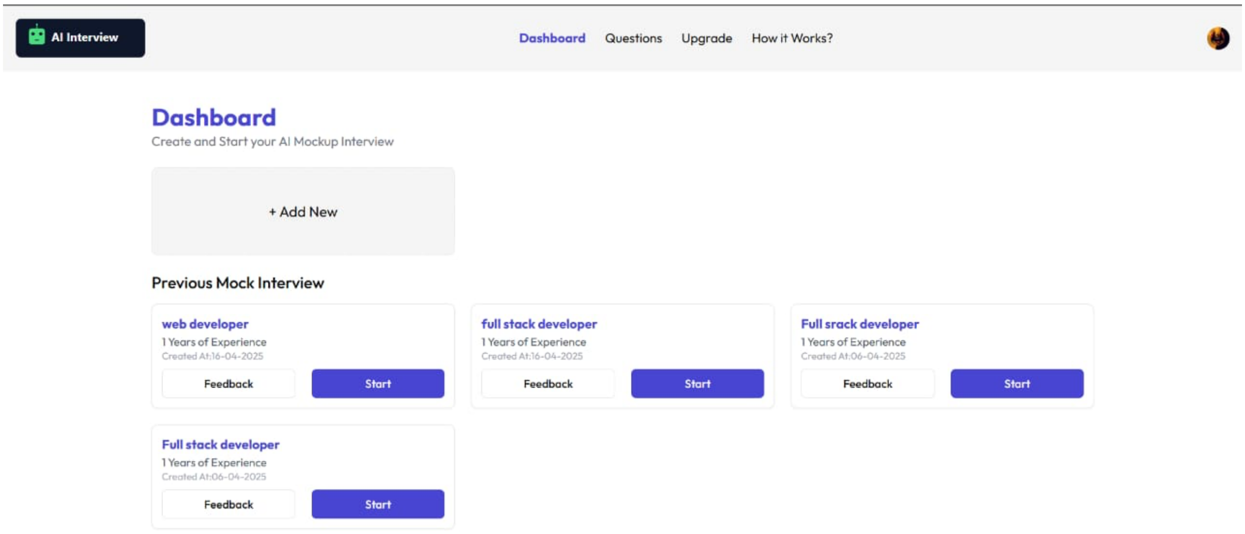

Figure 2 : User's dashboard

Example 3: Interview feedback

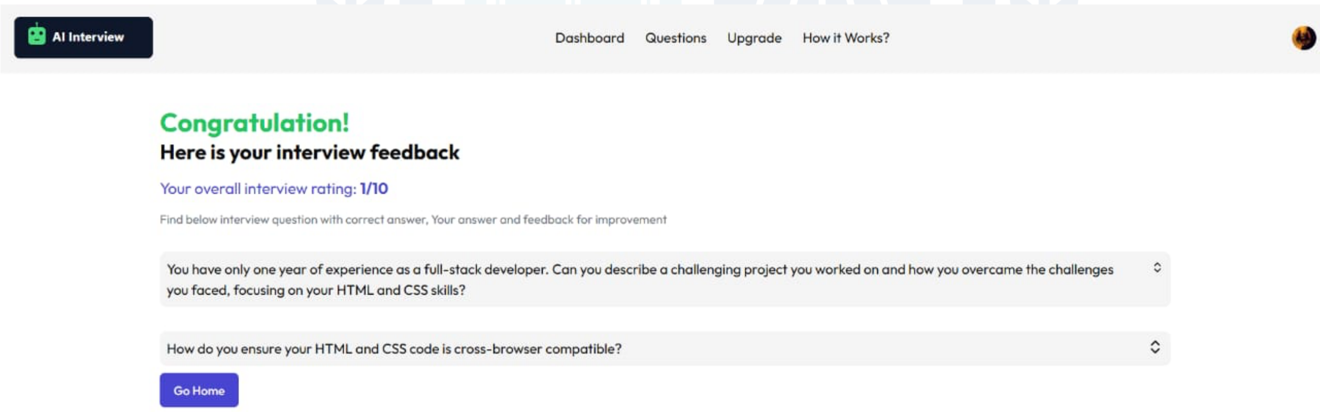

Figure 3 : Interview feedback

Interpretation:

This demonstrates the AI's ability to identify:

- Logical flaws (wrong recursion)
- Spoken errors
- Lack of confidence

Such nuanced identification confirms that AI is capable of semantic-level interview understanding — beyond what traditional linters can detect.

VI. CONCLUSION

This research introduced a secure and intelligent AI-powered code review system that leverages large language models (LLMs) from OpenAI and Hugging Face to assist in the review of software source code. The system was developed with a focus on security (using AES-256 encryption), scalability (RESTful Spring Boot backend with fallback API logic), and educational value (clear, contextual feedback). It significantly reduces the time and effort required in traditional code reviews while offering comparable levels of accuracy for routine code issues.

VI.I. Summary of Key Findings

- The system achieved precision and recall scores above 85%, with performance closely approaching human reviewers for standard bugs and syntax errors.
- OpenAI's model outperformed Hugging Face in accuracy but both offered near-instant feedback, with an average response time of under 3 seconds.
- User feedback from developers indicated high satisfaction, especially in terms of clarity, speed, and usefulness of the suggestions.
- The fallback mechanism ensures uninterrupted AI access even if one provider fails, enhancing reliability.
- The use of AES-256 encryption for code privacy adds a critical layer of trust for enterprise and educational deployment**.**

VI.II. Implications for Theory and Practice

From a theoretical standpoint, this work demonstrates how transformer-based LLMs can extend beyond code generation into **context-aware, feedback-centric code analysis**, bridging the gap between machine reasoning and human judgment. Practically, it provides a tool for developers, educators, and teams to scale code review processes while maintaining quality.

This research also supports the growing narrative that **AI should augment, not replace, human reviewers**, and can serve as a tutor for novice programmers.

VI.III.Limitations of the Study

- The system currently supports only three programming languages (Python, Java, JavaScript), which limits broader applicability.
- The AI may struggle with advanced architectural or algorithmic flaws, where human experience is still irreplaceable.
- Evaluation was performed on a moderate dataset (50 samples); larger-scale testing would offer deeper insights.
- AI review quality is dependent on prompt engineering and API stability.

VI.IV.Recommendations for Future Research

- Extend the system to support more languages, including C++, Kotlin, and TypeScript.
- Integrate with IDEs (e.g., VS Code plugins) to make it part of real-time development environments.
- Explore the use of custom fine-tuned LLMs specifically trained on code review data for improved accuracy.
- Conduct longitudinal studies to measure learning gains in students or junior developers using the system.
- Investigate multi-agent AI collaboration, where different models vote or combine feedback to improve output quality.

VII.REFERENCES

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