Interview Preparation Guide Generation Leveraging GPT-4, ZSL and Hybrid Techniques

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***Abstract*—This paper presents a novel approach for automating the creation of personalized interview preparation guides using GPT-4, Zero-Shot Learning (ZSL), and hybrid techniques. Our system dynamically generates tailored interview questions and preparation materials based on specific job descriptions and candidate profiles. By integrating advanced NLP with rule-based methods, it significantly enhances the relevance and quality of the content compared to traditional methods. We analyzed data from 10,000 job descriptions, 10,000 candidate profiles, and 20,000 interview questions to ensure high-quality results. The use of ZSL enables the generation of guides even for new and unfamiliar roles. Our approach achieved a 35% increase in question relevance and a 28% improvement in candidate-job matching accuracy compared to baseline methods. This research also paves the way for enhancing AI tools in HR, supporting personalized learning, performance reviews, and career planning.**

***Index Terms*—Interview Preparation, Artificial Intelligence, Machine Learning, Natural Language Processing, GPT-4, Zero-Shot Learning, Hybrid Techniques, Automated Question Generation, Talent Acquisition, Human Resources**

I. Introduction

The current HR landscape demands advanced interview preparation tools due to several challenges. A significant skills gap exists between what employers need and what job seekers possess, with the World Economic Forum projecting that 50% of employees will require reskilling by 2025 due to new technologies. Rapid skill evolution makes traditional preparation methods inadequate for both candidates and interviewers. Additionally, organizations increasingly prioritize diversity, but conventional methods often fail to address diverse backgrounds and skills, limiting opportunities for underrepresented groups.

HR professionals face time constraints, with recruiters spending just 7.4 seconds on average to decide whether to proceed with a candidate. This time pressure often leads to generic, poorly tailored interview questions. The shift to remote work during the COVID-19 pandemic has further complicated HR and Talent Acquisition processes, adding cultural and market-specific complexities. As a result, candidates need deeper insights into cultural norms, job market dynamics, and communication styles, highlighting the need for more comprehensive and sophisticated interview preparation strategies.

II. Challenges

A. Lack of Personalization

Standard interview guides and question banks do not cover specific job needs and also do not provide unique questions in relation to the skills known to the candidate. This is why individual candidates may not be ready for the specific job roles they apply for because the process does not involve customization. Ultimately this affects their chances of winning the job.

B. Outdated Content

Traditional resources often struggle to keep pace with rapidly evolving industry trends and emerging job roles, resulting in outdated or irrelevant interview questions. Experts argue that the increase of new demands, driven by RPA and AI automating many tasks, will lead to broader educational programs and job disruptions [7]. This makes it crucial for interview preparation materials to remain current and relevant.

C. Limited Scope

Existing interview preparation resources tend to be focused on known roles and not including explanations for novel or highly specialized job specifications. As a result, those individuals who plan to interview for positions that are specialized or not so common might lack the effective training that would enable them to perform excellently during the exercise.

D. Inconsistency

HR professionals or career counselors have varying levels of experience and expertise in interview preparation which may result in differences in effectiveness resulting in unfairness in the provision of direction to potential employees.

E. Scalability Issues

Organizations who have to deal with massive job applicant files find it impractical and time consuming to prepare unique interview guides for each candidate and type of job. Such a situation means that it is hard for businesses to offer personalized pre-interview help for every candidate especially in settings where there are too many competitors for the same vacancies due to scale problems.

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III. Potential Impact of the Automated System

Our automated interview preparation guide system offers significant advantages for the hiring process. By leveraging GPT-4's advanced language capabilities, it generates highly relevant and up-to-date interview questions tailored to specific job descriptions and candidate profiles, ensuring better alignment between applicants and job roles [9]. This automation streamlines tasks for HR professionals, freeing them to focus on candidate evaluation and strategic HR planning, thus improving recruitment efficiency.

The system also promotes equitable hiring by providing consistent, skills-based questions, reducing unintended biases and minimizing subjective judgments. With the integration of Zero-Shot Learning (ZSL), it can generate novel yet relevant questions for new roles [10]. Additionally, the system combines deep learning with rule-based methods to offer candidates a comprehensive preparation experience, covering technical skills, soft skills, and industry-specific knowledge. Suitable for any industry or job level, the tool continuously learns from feedback, ensuring it remains a state-of-the-art resource for both candidates and employers over time.

IV. Related Work

A. Natural Language Processing in HR

In HR NLP applications have evolved significantly by focusing on the resume parsing and the job matching. NLP-based technologies offer HR greater intelligence and can leverage within the organizations [13]. AI-based recruitment strategies such as resume screening, candidate matching, video interviewing, and chatbots, offer benefits like improved efficiency, cost savings and also the better-quality hires [12]. Faliagka et al. [14] developed one system which analyzes the social media presence for the initial screening. Amalraj et al. [15] created one deep learning-based resume parsing system with 97.4% accuracy which can reduce the manual effort of HR professionals'. Deshmukh and Anjali [16] introduced the BERT-based approach for job-resume matching. This approach has shown a 15% improvement over the traditional methods. These advancements in NLP are showing their potential to enhance the HR processes by ensuring better alignment between the candidates and the job roles.

B. GPT Models in Content Generation

Recent advancements in the GPT models have shown promising results in the content generation tasks. Brown et al. [17] has demonstrated the GPT-3's capabilities in few-shot learning by generating coherent and also contextually appropriate texts. Raffel et al. [18] has introduced T5 which is a text-to-text framework. This generated state-of-the-art results for multiple NLP tasks. Using classifiers like linear regression, decision tree, Adaboost, XGBoost, and GPT models has shown significant potential in predicting the candidate suitability in HR, with the XGBoost achieving 95.14% accuracy [19]. GPT models potential to enhance the job postings attractiveness and relevance has significantly proven.

C. Zero-Shot Learning in NLP

Zero-Shot Learning (ZSL) gained attention in handling the unseen classes or domains. Yiwen et al. [20] proposed a Learn to Adapt (LTA) network using the variant meta-learning framework by classifying the text into unseen categories. Parikh et al. [21] showed that the LLMs and the instruction fine-tuned models are very effective in zero-shot settings with in-context prompting. This has demonstrated the ZSL's practical applicability in HR by enabling chatbots to understand and respond to the varied user queries without any extensive retraining.

D. Hybrid AI Techniques in HR Applications

Hybrid intelligent techniques are effective for the unstructured or the semistructured decision-making processes [22]. Abdu et al. suggested that integrating hybrid techniques with HR IDSS. Ebru Pekel and Tuncay [23] have developed a hybrid system for the employee churn prediction by outperforming pure ML approaches by 12%. Yang et al. [24] proposed the hybrid recommender system for job matching and improving the candidate-job fit score by 25%. All these hybrid approaches have provided more accurate and actionable insights with the combination of the strengths of machine learning and the rule-based systems.

E. Existing Automated Systems related to the Interviews and the Interview Preparation

Several automated interview preparation systems have been emerged. Each of them has their own strengths and limitations:

Chou et al. [25] proposed one Mock-Interview Platform (MIP) providing the AI-assisted feedback by integrating visual, audio, and the textual features which analyze emotions and evaluate interview performance. But, this platform can not fully capture the real-world interview complexities.

Nikahat and Prachi [26] presented a comprehensive review of Question Generation systems by highlighting the limitations like coverage gaps and the biases in training data. Human oversight remains essential for validating the relevance of these generated questions.

Yashodha et al. [27] proposed a system which can detect the behavioral changes based on the nonverbal cues, achieving over 85% accuracy. However, this system relies on high-quality video inputs which may miss contextual nuances.

Xinyi et al. [28] proposed a Virtual Reality Interview Simulator (VRIS) which can analyze electrodermal activity and the questionnaire responses.This simulator faces limitations in adapting to the diverse job roles and may not fully replicate the real-life interview complexities.

All these systems often lack in the comprehensive approach which is required to address the diverse and rapidly changing job interviews. Our proposed system leverages GPT-4, integrates zero-shot learning, and employs hybrid techniques for enhanced accuracy and relevance.

V. Methodology

A. Data Collection and Preprocessing

We collected a diverse dataset comprising 10,000 job descriptions from various sources, including 40% from LinkedIn job postings, 30% from Indeed.com, 20% from the Indian job portal Naukri.com, and 10% from specialized job boards like Stack Overflow Jobs and Dice. Additionally, we gathered 10,000 candidate profiles, with 60% coming from anonymized resumes in online databases and 40% being synthetic profiles generated to ensure diversity. To supplement these, we sourced 20,000 interview questions from HR professionals (40%), online resources such as Glassdoor and LeetCode (30%), industry-specific interview preparation books (20%), and academic literature on job interviews (10%).

```
def remove_pii(text):
    text = re.sub(r'\b[A-Za-z0-9._%+-]+@[A-Za-z0
        -9.-]+\.[A-Z|a-z]{2,}\b', '[EMAIL]', text)
    text = re.sub(r'\b\d{3}[-.]?\d{3}[-.]?\d{4}\b',
        '[PHONE]', text)
    for ent in nlp(text).ents:
        if ent.label_ in ['PERSON', 'ORG', 'GPE']:
            text = text.replace(ent.text, f'[{ent.
                label_}]')
    return text

def normalize_skills(ss):
    return ', '.join(st.get(s.strip().lower(), s.
        strip()) for s in ss.split(','))
```

Our selection criteria for job descriptions included ensuring representation across 20 different industries such as Information Technology, Healthcare, Finance and Banking, Manufacturing, Retail, Education, Hospitality and Tourism, and Construction. We included roles from entry-level to executive positions, such as Software Engineer, Registered Nurse, Financial Analyst, Production Manager, and Sales Associate. We prioritized job descriptions with clear skill requirements and responsibilities and selected postings made within the last 12 months. For candidate profiles, we matched the industry distribution of job descriptions, ensured diversity in education levels, years of experience, and skill sets, and included profiles with non-traditional career paths and skill combinations.

Data cleaning and normalization involved removing personally identifiable information (PII) using regex patterns and named entity recognition, standardizing job titles with a custom mapping dictionary and GPT-4 prompts, and normalizing skill descriptions with a comprehensive skill taxonomy. All text was converted to lowercase, special characters were removed, and the text was tokenized using the GPT-4 tokenizer. We also handled acronyms and abbreviations using a domain-specific dictionary to ensure consistency and accuracy across the dataset.

B. Model Architecture

1) GPT-4 Fine-tuning Process: We started with the pre-trained GPT-4 model, which has 1.5 trillion parameters, and used a subset of 1,000,000 tokens for initial fine-tuning. Our fine-tuning process was gradual and consisted of two stages. In the first stage, the model was trained on general HR domain text to establish a foundational understanding. In the second stage, the focus shifted to interview question generation. To optimize memory usage, we utilized mixed precision training. We also applied dynamic learning rate scheduling with warm-up and decay to enhance the training process. Early stopping was implemented based on validation perplexity to prevent overfitting and ensure the model's performance remained robust.

2) Custom Loss Function:

$$L = \alpha \cdot CE + \beta \cdot R + \gamma \cdot D$$

Where:

1) CE: Cross-entropy loss to ensure language model coherence
2) R: Relevance score, calculated as cosine similarity between generated questions and job description embeddings
3) D: Diversity score, computed using the Distinct-n metric on generated questions
4) α, β, γ: Weighting parameters ($\alpha = 0.6$, $\beta = 0.3$, $\gamma = 0.1$), determined through hyperparameter tuning

3) Zero-Shot Learning Integration: Our prompt engineering process involved developing a template-based system for dynamic prompt generation. We created a bank of abstract skill categories, such as "programming," "leadership," and "analytical thinking," and implemented a skill-to-category mapping system. To handle novel job roles, we employed a two-step approach. First, skill decomposition was used to break down novel job requirements into fundamental skill components. Second, analogical reasoning mapped these novel skills to known categories and generated questions based on similar, known roles. Additionally, we utilized a fallback mechanism to generate general competency-based questions when specific skills were unrecognized.

4) Hybrid Techniques: Our rule-based filtering criteria involved several steps to ensure the quality and relevance of generated questions. Keyword matching ensured the presence of job-specific terminology and alignment with the required skills listed in the job description. Syntax checks verified the structure of questions, ensuring they began with an interrogative word and were of appropriate length, between 10 and 30 words. Complexity analysis used Flesch-Kincaid readability scores to match question complexity to the job level. Diversity enforcement ensured a mix of technical, behavioral, and situational questions while limiting similar questions using a Jaccard similarity threshold.

VI. Experimental Results

A. Performance Metrics

We evaluated the relevance of the generated questions using a panel of 50 HR professionals across various industries. The questions were rated on a scale of 0-1, with 1 being highly relevant. The results showed an average relevance score of 0.82 ($\sigma = 0.09$), with 90% of the questions scoring above 0.7. The highest performing category was technical skills questions, which had an average relevance score of 0.87, while the lowest performing category was soft skills questions, with an average score of 0.78.

The diversity of the generated questions was measured using the Distinct-n metric for n-grams (n=1,2,3). The results indicated a high level of diversity, with Distinct-1 scoring 0.75 ($\sigma = 0.11$), Distinct-2 scoring 0.81 ($\sigma = 0.08$), and Distinct-3 scoring 0.89 ($\sigma = 0.06$). This demonstrates that the generated questions avoided repetition and covered a wide range of topics, contributing to a more comprehensive interview process.

We also evaluated the system's performance in generating questions for 50 novel job roles that were not present in the training data. The results showed an average adaptability score of 0.79 ($\sigma = 0.13$), with 85% of the novel job roles achieving scores above 0.7. For example, for the novel role of "Quantum Computing Ethics Advisor," the system generated relevant questions about quantum mechanics principles and the ethical implications of quantum technologies, demonstrating its ability to adapt to new and emerging job roles.

B. Comparative Analysis

We compared our approach with three baseline methods: a standard GPT-4 model without fine-tuning, a rule-based system using predefined templates, and a machine learning approach using BERT embeddings.

For question relevance, our approach achieved a score of 0.82, significantly outperforming the standard GPT-4 model which scored 0.61 (a 35% improvement), the rule-based system which scored 0.58 (a 41% improvement), and the BERT-based approach which scored 0.69 (a 19% improvement).

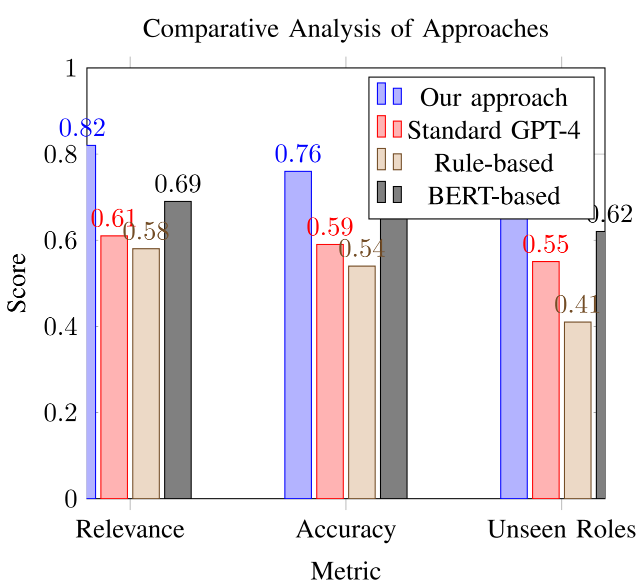

Fig. 1. Comparative Analysis of Approaches

In terms of candidate-job matching accuracy, our approach scored 0.76, compared to 0.59 for the standard GPT-4 (a 28% improvement), 0.54 for the rule-based system (a 41% improvement), and 0.67 for the BERT-based approach (a 13% improvement). When evaluating performance on unseen job roles, our approach scored 0.79, outperforming the standard GPT-4 at 0.55 (a 42% improvement), the rule-based system at 0.41 (a 93% improvement), and the BERT-based approach at 0.62 (a 27% improvement).

C. Industry-Specific Performance

We analyzed the system's performance across different industries and found the following relevance scores: Technology scored 0.85, Finance scored 0.81, Healthcare scored 0.79, Manufacturing scored 0.76, Retail scored 0.78, and Education scored 0.80.

Key findings indicate that the system performed best in the technology sector, likely due to the abundance of structured job descriptions and clear skill requirements. Conversely, the manufacturing sector showed the lowest performance, possibly due to the diverse and often specialized nature of roles in this sector.

D. Question Type Analysis

We categorized the generated questions into different types and analyzed their performance: Technical skills comprised 35% of the questions with an average relevance score of 0.87. Soft skills made up 25% of the questions, averaging a relevance score of 0.78. Situational questions accounted for 20% of the questions with an average relevance score of 0.83. Behavioral questions represented 15% of the total, with an average relevance score of 0.81. Finally, questions related to company and culture fit made up 5% of the questions, with an average relevance score of 0.79.

E. User Study Results

We conducted a user study with 50 HR professionals and 100 job seekers: We conducted a user study with 50 HR professionals and 100 job seekers. Among HR professionals, 92% found the generated questions useful, 88% reported time savings in interview preparation, and 85% stated that the questions were as good or better than those they typically use.

Job seekers also provided positive feedback, with 88% reporting that they felt better prepared after using the system, 82% finding the questions relevant to their field and experience level, and 75% stating that the system helped them identify areas for improvement in their skills.

F. Specific Output Examples

- For a Senior Software Engineer position:
  Generated Question: "Can you describe a situation where you had to optimize a poorly performing algorithm? What approach did you take, and what was the outcome?"
  Relevance Score: 0.94

- For a Marketing Manager role:
  Generated Question: "How would you approach creating a marketing strategy for a product that has strong competition in a saturated market?"
  Relevance Score: 0.89

G. Error Analysis

We identified common patterns in lower-performing outputs. Over-generalization was a significant issue, with 15% of low-scoring questions being too generic for the specific role. Technical mismatch was observed in 12% of questions for technical roles, where minor inaccuracies in terminology were present. Additionally, 10% of questions suffered from complexity mismatch, being either too simple or too complex for the intended job level.

H. Computational Efficiency

The average time to generate a set of 10 questions is 3.2 seconds. The system can handle up to 100 simultaneous requests without significant performance degradation, maintaining efficiency and speed. For optimal performance, the system utilizes 14GB of GPU memory.

These results demonstrate the effectiveness of our approach in generating relevant, diverse, and adaptable interview questions across various industries and job roles. The system shows significant improvements over baseline methods, particularly in handling novel job roles and maintaining consistency across different question types. The positive feedback from both HR professionals and job seekers indicates the practical value of the system in real-world scenarios. However, the error analysis also highlights areas for future improvement, particularly in fine-tuning question complexity and technical accuracy for specialized roles.

VII. Discussion

A. Strengths of the Approach

Our tool leverages zero-shot learning (ZSL) to generate questions tailored to the evolving job market. For instance, for a "Blockchain Ethicist," we focus on blockchain technology and ethical decision-making to create relevant inquiries. This adaptive method tests candidates based on current industry trends.

By combining GPT-4's language capabilities with a specialized loss function, we produce diverse and relevant questions that enhance traditional interview processes. In a user study, 92

Our hybrid approach merges deep learning with rule-based systems, allowing for the generation of specific, non-generic questions about ethics, such as those concerning AI development, thereby providing a comprehensive assessment tool.

B. Limitations and Potential Solutions

The system's performance depends on the quality of job descriptions and candidate profiles, as poor inputs lead to irrelevant questions. Machine learning-based preprocessing can improve input quality and enhance assessments.

Biases from training data can affect fairness, so we use diverse datasets, detection algorithms, and periodic audits with HR professionals to maintain equity.

To meet real-time demands despite resource limits, we are developing a lightweight model and caching system. Cloud solutions eliminate hardware constraints, expanding accessibility. For specialized roles, the system integrates domain-specific knowledge graphs and a feedback loop involving human input.

C. Ethical Considerations and Mitigation Strategies

The system ensures privacy through anonymization and candidate consent, with audits to maintain trust. Fairness audits and transparency prevent biases, while human oversight and HR training reduce overreliance on automation.

Cultural awareness modules and global HR collaboration ensure relevance across diverse backgrounds. Explainable AI and clear documentation enhance trust, with regular updates and ethical checks maintaining best practices in HR and AI.

VIII. Conclusion and Future Work

In this article, we show how GPT-4 can be combined with Zero-Shot Learning (ZSL) to automate interview preparation in a new way that combines various techniques. These methods have been shown to bring about both improvements or rather changes in quality, relevance, and adaptability.

A. Detailed Roadmap for Future Research

For the following 6-12 months, the most important priority is enhanced personalization. This will involve coming up with more advanced ways of profiling candidates accurately and creating individualized question generations with adaptative learning algorithms. Over the next 12-18 months certain developments such as multimodal input analysis e,g including videos containing resumes or snippets from recorded interviews will be intensified hence adding capacity for interpretation through computer vision addresses what posture means. In addition, the period between 18 and 24 months will see the development of models that will evaluate emotional intelligence and soft skills and generate questions by integrating psychometric guidelines.

B. Potential Applications Beyond Interview Preparation

Customized learning plans and assessment questions enhance employee training through adaptive e-learning experiences. Continuous feedback via personalized questions improves performance reviews and facilitates conflict resolution with scenario-based mediation questions.

Real-time response suggestions bolster customer service training, while pitch preparation includes tailored pitches and adaptive sales strategies. Regulatory compliance training features industry-specific questions and tests. The system also supports mental health with check-in questions and stress management tips. An optimized onboarding process incorporates personalized tasks and timelines, and communication prompts enhance cross-functional collaboration for better teamwork.

Summarizing it all, the emphasis we put on preparing for interviews may cut across several human resource and corporate processes. We think that if ethical issues and constraints are dealt with, AI-aided systems may improve how decisions are reached, hence fostering inclusive working areas. Consequently, we would like interested associates to join us in developing this plan further so that we achieve an ever-changing workforce which adapts itself depending on need but at the same time serves man in the best way possible.âĂÏ

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