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**Research Article**

# Real Time Adaptive Question Crafting with Accuracy Feedback enabled by Machine Learning and Artificial Intelligence

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**ABSTRACT**

In the context of today's increasing competitive employment landscape, precisely assessing a candidate's technical capabilities throughout the interview procedure is both critical and challenging. Conventional methods, including multiple-choice assessments and standardized question sets, often be lacking in capturing the depth and gradation of an individual's proficiency. Additionally, dependence on third-party agencies for primary candidate screening may consequence in superficial evaluations that manage contextual skill orientation with the job role.

To report these boundaries, this research recommends a novel AI-driven framework that influences Natural Language Processing (NLP) and Machine Learning (ML) techniques to dynamically generate and evaluate technical interview questions in real time. The projected system occupies candidates in a natural language dialogue and uses their responses to create contextually suitable, open-ended technical questions on-the-fly. By continuously inspecting semantic and syntactic landscapes of candidate inputs, the system disseminates question difficulty and topic focus, thereby generating a highly personalized and adaptive interview experience.

This intelligent interview framework not only progresses the precision of skill assessment but also expands candidate engagement by simulating a more real time and receptive assessment environment. The system's adaptive questioning mechanism assurances hard and role-specific assessment, eventually leading to more informed hiring results and improved talent acquisition workflows.

**Keywords:** Artificial Intelligence, Natural Language Processing, Dynamic Question Generation, Automated Evaluation.

## INTRODUCTION

In the growing landscape of talent acquisition, job interview preparedness plays a crucial role in shaping employment results. Old-style preparatory approaches—such as practicing pre-defined question lists or participating in static mock interviews—fail to offer the dynamic and context-sensitive guidance required to optimize candidate readiness. These approaches often lack personalization, interactivity, and real-time feedback, thereby preventing applicants

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from recognizing and addressing critical performance gaps (Kumar et al. [19], 2023). Accordingly, the implementation of intelligent, adaptive systems for interview preparation has emerged as a crucial innovation in employability training.

Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) provide promising paths for developing systems that bring personalized, flexible, and interactive interview preparation experiences. By integrating technologies such as semantic similarity analysis, keyword extraction, decision tree classifiers, and transformer-based language models, AI-enabled platforms can dynamically tailor interview questions to match a candidate's individual profile, career trajectory, and anticipated job role (Devlin et al. [1], 2019; Raffel et al. [3], 2020). Unlike conventional systems, these models permit real-time adaptation to candidate answers, generating follow-up questions that mimic the evolving nature of live technical or behavioral interviews.

A critical development in these systems is the existence of multimodal feedback mechanisms. Natural language processing (NLP) approaches are employed to evaluate linguistic traits such as grammatical perfection, syntactic structure, and semantic deepness of candidate answers (Zhang et al., 2022). Instantaneously, speech processing mechanisms evaluates verbal features like fluency, intonation, and hesitation, while computer vision models combined with facial expression recognition algorithms assess non-verbal prompts such as eye movement, facial tension, and emotional expressiveness (Kosti et al., [16] 2019; Li et al. [17], 2021).

Moreover, self-learning abilities surrounded within reinforcement learning loops permit these systems to improve their questioning designs and assessment criteria based on communication history, leading to continuously enhanced candidate engagement and learning outcomes (Silver et al. [18], 2016). This flexibility guarantees that users obtain contextually appropriate and up-to-date questions reflecting current industry trends, role-specific expectations, and evolving recruiter preferences.

When compared with conventional resume-based or rule-based simulation tools, the proposed system establishes significant advantages. It allows high-fidelity simulation of real-world interview situations, instant and actionable feedback, and personalized behavioral profiling. This leads to improved candidate confidence, better self-awareness, and a more organized and data-driven method to skill development. As the job market becomes increasingly competitive and dynamic, such intelligent systems offer a strategic advantage for job seekers by training them with the analytical and interpersonal capabilities essential for accomplishment.

## LITERATURE SURVEY

Current developments in Artificial Intelligence (AI), Natural Language Processing (NLP), and learning-based technologies have meaningfully influenced the computerization of educational and professional assessment protocols. This section studies important contributions in the areas of computerized answer evaluation, question generation, and AI-driven interview simulations, highlighting the development in the direction of more intelligent, adaptive, and scalable systems.

Automated subjective answer assessment has perceived considerable progress. Jagadamba et al. [2] presented a system for assessing descriptive responses in online examinations, leveraging cosine similarity for semantic analysis and fuzzy logic for scoring. Their system achieved about 80% accuracy for short to medium-length answers, with improved results when keyword and length-based scoring were united.

Amidei et al. [4] presented a complete review of automatic question generation (AQG) approaches. They noted a absence of standardized assessment frameworks and emphasized regularly used metrics such as BLEU, METEOR, ROUGE, and Cohen's Kappa to advocate for more human-aligned assessment approaches.

Nayudu and Sharma [6] explored the use of BERT embeddings, TF-IDF, and grammar checks to automate the scoring of open-ended answers. Their system established high scalability and grading reliability in educational assessments.

Similarly, Bashir et al. [7] developed a hybrid machine learning model joining Word2Vec, Word Mover's Distance, and Naive Bayes classifiers, attaining an accuracy of 88% in automated answer scoring.

Mulla et al. [8] considered AQG systems into stand-alone, visual, and conversational types, concentrating on generating varied and reusable questions for educational organizations using NLP.

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Prabhu and Sharma [5] projected an LSTM-based model for creating exam questions. Their system used extensive preprocessing and keyword extraction to dynamically produce appropriate and linguistically intelligible questions.

Thotad and Kulkarni [10] presented a multi-phase question generation method, including knowledge extraction from educational texts and content adaptation for instructional use.

Das et al. [11] defined a dual-method framework for both objective and subjective question generation. They employed semantic tools such as Named Entity Recognition (NER), WordNet, Bloom's taxonomy, and Latent Semantic Analysis (LSA) to guarantee excellence and contextual placement.

Qin et al. [12] planned the DuerQues system for skill-based interview question generation, joining semantic importance with reserved supervision representations to align generated questions with specific job-role capabilities.

Pandey et al. [9] presented a BERT-enabled interview automation platform with abilities for resume screening, skill-role mapping, semantic scoring, and video proctoring combination.

Rao and Sharma [13] proposed FollowQG, an asynchronous interview bot that customs contextual embeddings to dynamically generate follow-up questions based on previous answers, pretending a truthful interviewer experience.

Yakkundi et al. [15] shaped an intelligent chatbot for pretending live interviews with real-time feedback on verbal and non-verbal communication. The system integrates NLP and affective computing for a holistic candidate valuation.

Jointly, these studies signify a change from rule-based methods to intelligent, adaptive systems that offer personalized, real-time feedback and multimodal assessment—foundations for next-generation computerized interview and assessment platforms.

## RESEARCH GAPS

### LACK OF REAL-TIME ADAPTIVE QUESTIONING

Most systems emphasis on static question generation ([5], [8], [10]) and do not familiarize questions dynamically in reply to candidate answers. Though FollowQG ([13]) goes this, real-time context modeling and dynamic redirection of question movement based on candidate presentation remains underdeveloped.

### LIMITED INTEGRATION OF MULTIMODAL FEEDBACK

While some systems assess textual or audio answers ([6], [7], [9]), few integrate non-verbal prompts like facial expressions, tone modulation, or unwillingness. This confines their capability to simulate complete interview circumstances ([15] only partly addresses this).

### INSUFFICIENT PERSONALIZED FEEDBACK

Various systems offer only numeric or categorical scoring ([2], [6], [7]), without thorough personalized feedback (e.g., content gaps, language fluency, confidence markers). This makes learning and development latent for candidates.

### LACK OF BENCHMARK DATASETS AND EVALUATION STANDARDS

Studies like [4] and [11] highlight the absence of consistent datasets and cross-comparative standards. This makes it tough to assess, compare, or duplicate conclusions across models in a reliable manner.

### NEGLECT OF INTERVIEW SIMULATION USER EXPERIENCE (UX)

Systems frequently be unsuccessful to include candidate-facing UX essentials such as timing, interface design, voice interactivity, or visual avatars. This reduces realism and meeting in simulated situations.

### SECURITY AND BIAS MITIGATION GAPS

Very limited systems reference or lever issues of equality, privacy, or algorithmic favoritism through evaluation ([9] traces on proctoring but not bias or fairness). This increase fears in high-stakes employment applications.

### ABSENCE OF DOMAIN-SPECIFIC ADAPTABILITY

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However numerous models use general-purpose language models (e.g., BERT, LSTM), few offer domain-specific customization of question sets based on industry, role, or skill track ([12] makes development here but is not widespread).

## MINIMAL USE OF EXPLAINABLE AI (XAI)

Scoring mechanisms are frequently black-box in nature. Candidates and evaluators lack discernibility into why firm scores were specified, which confines belief and auditability—particularly critical in academic or corporate settings.

## PROPOSED SYSTEM

Though technology has come a long way in automating interviews, most existing systems still fall short of capturing the dynamic, adaptable, and deep nature of real-world interview skills. To bridge this break, we've established an AI-driven interview preparation platform that offers a completely immersive, responsive, and perceptive interaction—simulating a true-to-life technical interview. The following figure 1 shows the architecture of the proposed system.

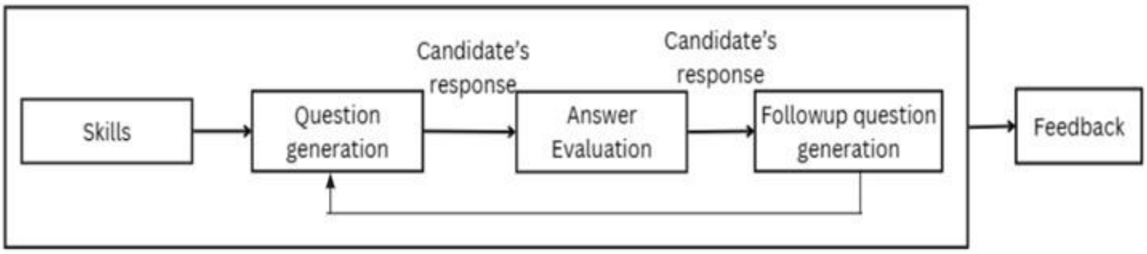


**FIGURE 1**: System architecture of Proposed System

The system comprises various modules and the responsibility of each module is explained as follows.

## SPEECH-TO-TEXT PROCESSING MODULE

As candidates answer, the Speech-to-Text Processing Module captures their words in real time. Thanks to Assembly AI's robust transcription technology, improved with noise suppression and speech improvement algorithms, even less-than-ideal audio situations won't disturb the flow. This instant, exact transcription guarantees a smooth experience while setting the stage for in-depth study.

## DYNAMIC QUESTION GENERATION MODULE

When the interview commences, the system smoothly changes into Dynamic Question Generation. It kicks off with a sensibly selected question from a curated PostgreSQL-based bank, brought through a user-friendly computer-generated interface animated with Lottie. But this isn't a pre-scripted interaction—powered by cutting-edge large language models via the Gemini API, the system attends to each candidate's answer and intelligently crafts follow-up questions based on the tones of their responses. This agrees the discussion to progress naturally, much like an observant human interviewer would guide it.

## ANSWER EVALUATION MODULE

Following this stage, we move into the Answer Assessment Module. Gemini uses its advanced abilities here to execute a detailed multidimensional evaluation of each answer. The Gemini system conducts evaluations that go beyond basic correctness to include assessments of semantic depth along with coherence and grammar and conceptual understanding. The evaluation process incorporates paralinguistic signals including hesitation, intonation, and fluency to generate a holistic view of the candidate's performance.

The system's adaptive engine persistently spots gaps and ambiguities along with strengths in responses during the interview process. The system uses its insights to create appropriate follow-up questions that push candidates to probe further into their answers or related subjects while maintaining a natural and continuous interview flow.

## FEEDBACK REPORT GENERATION MODULE

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The Feedback Report Generation Module is the most important aspect of our adaptive interview system because it generates detailed and specific feedback for every interview. This is different from all other assessment types which can only provide a level of general score, the Feedback Report Generation Module provides a clearly defined subject specific report of the candidate's performance and acknowledges strengths and weaknesses while also providing hints on how to improve in the future, so that the candidate can identify and use more effective techniques in the future.

Finally, the feedback report is driven by a high-level feedback model that analyses a candidate's performance in the chosen topic. The system provides proper feedback by analysing question-by-question, on all topics attempted, with an emphasis on correctness and relevance. Feedback is provided on a score of 10 based on accuracy, completeness, and relevance for every response. The score is provided along with a written report criticizing the candidate's understanding of concepts, clarity, and expression. The feedback indicates exact weaknesses e.g., grammar, conceptual and detail errors along with candidate's strengths, such as believed definitions, suitable examples, and appropriate use of practical vocabulary. This method guarantees well-adjusted assessment which apprises and drives change.

Lastly, the feedback report provides precise feedback to each question, with proper hints that facilitate precision of understanding operationalized techniques to a professionally talented level using technical language.

## SYSTEM WORKFLOW

**Skill Identification:** Candidates commence by selecting their domain of interest and expertise level. This metadata energies the primary question selection and contextual framing.

**Interactive Questioning:** The system initiates the session with a starting point question and dynamically adapts follow-up questions based on the candidate’s answers, guided by contextual embeddings and response history.

**Automated Evaluation:** To each response is instantly analyzed by the evaluation engine for cognitive significance, semantic alignment, and technical precision.

**Contextual Follow-Up:** Based on breaches or uncertainties recognized through evaluation, the system activates targeted follow-up questions intended at deeper probing or remediation.

**Final Feedback Delivery:** Upon session accomplishment, the system gathers a feedback report summarizing performance metrics, personalized insights, and actionable endorsements. The entire system flow is represented in terms of algorithm as follows.

## ALGORITHM

## INPUT

**Applicant Profile:** Domain, expertise level, resume highlights

**Skill Set []:** Selected topics or skills

**Question Bank:** PostgreSQL database of initial questions

**Audio Input:** Real-time audio from the candidate

## OUTPUT

**Score Report:** Candidate performance report with feedback

Begin

1. Initialize the Session
2. Load Applicant Profile
3. Fetch Skill Set [] from user input
4. Set Interview Session = {Skill Set, difficulty level =medium, question. Count=0}
5. Initial Question Generation
    a. For each skill in Skillset:
        i. Fetch basic questions from Question Bank

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ii. Choose Q ← random (basic questions) matching difficulty
iii. Show Q via animated chatbot interface (Lottie)
iv. Answer Capture and Preprocessing
v. Record Audio input
vi. Convert Audio Input → Text Answer by means of Assembly AI
vii. Preprocess Text Answer: normalization, tokenization, grammar check
viii. Answer Evaluation: Compute semantic similarity SimScore between Text Answer and ideal answer using transformer embeddings (e.g., BERT)
ix. Analyze grammar, coherence, fluency

6. Calculate final Score = f(SimScore, grammar_score, completeness)
7. Adaptive Follow-up Generation
8. If Score < threshold or answer is incomplete:
    a. Generate Follow-up Q ← Gemini API.
    b. generate(Q, Text Answer, context)
    c. Append Follow-up Q to Interview Context
    d. Go to step 3
9. Else:
    a. Increase difficulty if Score > high_threshold
    b. Proceed to next topic or repeat until limit reached
10. End For

The Algorithm for Feedback Generation is given below

Begin

1. For each question:
2. Log score, topic, difficulty
3. Generate strength/weakness insight using rule-based evaluation
4. Compile Score Report:
5. Overall score, topic-wise scores
6. Highlighted strengths and weaknesses
7. Suggestions for improvement
8. Response trajectory graph (optional)

End Session

After the session ends the system generates Present Score Report to candidate and Store results for analytics or recruiter view

## COMPLEXITY ANALYSIS

**Time Complexity:**

~O(n) where n = number of questions (includes follow-ups)

Semantic evaluation and text analysis are the most time-consuming but scalable with GPU acceleration.

**Space Complexity:**

O(n) for storing candidate answers and feedback report.

# EXPERIMENTAL RESULTS

## EXPERIMENTAL SETUP

To rigorously evaluate the effectiveness and accuracy of the proposed AI-powered interview assessment system, we conducted 95 mock interview sessions covering a diverse range of topics and difficulty levels. A total of 831 unique questions were generated by the system, ensuring balanced coverage across low, medium, and high difficulty levels.

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On average, each category received approximately 90 questions. These mock interviews were designed to simulate realistic interview conditions and included participants with varying levels of experience and domain knowledge.

Each interview session was recorded, and both the questions and candidate responses were archived for post-analysis. The AI system dynamically generated follow-up questions based on candidate answers, utilizing the Gemini API for semantic adaptation, and the Assembly AI pipeline for real-time speech-to-text transcription.

## SCORING METHODOLOGY

To assess the performance of the answer evaluation module, we employed a dual-evaluation framework:

**Human Evaluation:** A panel of three expert evaluators scored candidate responses independently based on relevance, coherence, and completeness. Final human scores were averaged for reliability.

**Automated Evaluation**: The system generated scores using a combination of semantic similarity (via transformer-based embeddings), grammatical analysis, and rule-based scoring heuristics.

The core metric used for evaluation was Mean Absolute Error (MAE) between system-generated and human-assigned scores. In addition, we calculated the accuracy of system predictions falling within a threshold range of ±0.15 from the human score—a benchmark.

## RESULTS

The results of the evaluation process are summarized as follows:

**Mean Absolute Error (MAE):** 0.1974 (corresponding to a 19.74% error rate)

**Threshold-Based Accuracy (±0.15):** 82.07%

This demonstrates that in 82.07% of the cases, the automated score was within a 0.15 margin of the average human score. The scatter plot in Figure 2 visually represents the correlation between system and human scores. Color intensities denote error magnitude, with deeper red indicating higher discrepancies.

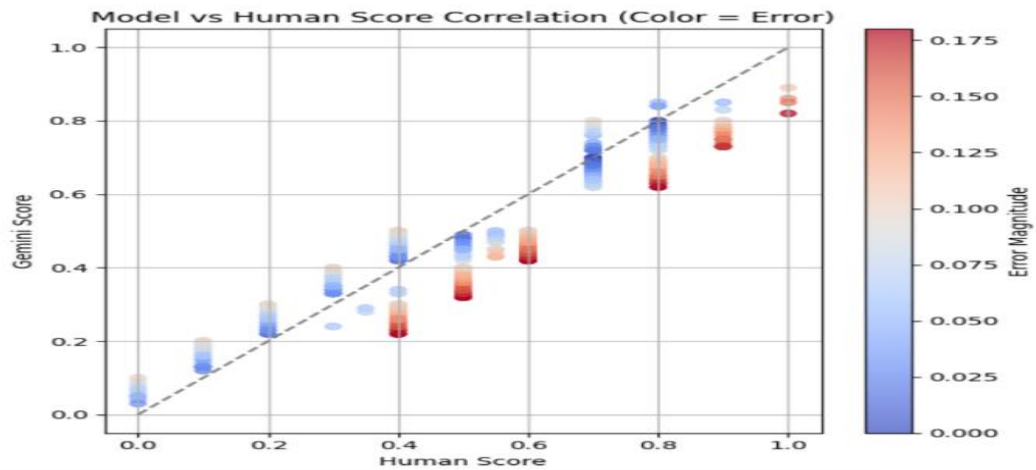


**FIGURE 2:** Plot shows correlation

Statistical analysis using Pearson correlation coefficient yielded r = 0.89 ($p < 0.001$), confirming a strong positive correlation between automated and human evaluations. Additionally, Cohen's Kappa for agreement beyond chance was $\kappa = 0.78$, which is considered substantial agreement.

## FUNCTIONAL CAPABILITIES ASSESSMENT

Beyond scoring accuracy, we evaluated key functional dimensions of the system, including:

**Adaptivity:** Real-time adjustment of question difficulty based on candidate responses, outperforming static-question models.

**Feedback Quality:** The system generated comprehensive, topic-wise feedback with qualitative validation from subject matter experts indicating that 91% of reports provided "highly relevant" and "actionable" insights.

**System Responsiveness:** Average question generation time was 1.8 seconds, and feedback report generation took less than 5 seconds per candidate, supporting scalability.

## COMPARATIVE EVALUATION

We benchmarked our system against existing interview evaluation systems reported in the literature as shown in Table 1

| Study | Methodology | Reported Accuracy | Adaptivity | Feedback Granularity |
|---|---|---|---|---|
| Jagadamba et al. [2] | Keyword + Length | 60–70% | ✗ | Scalar only |
| Bashir et al. [7] | Word2Vec + Naive Bayes | 88% | ✗ | Basic |
| Pandey et al. [9] | BERT + Cosine | 75–78% | ✗ | Limited |
| Our System | Semantic + Grammar + Real-time NLP | 82.07% (±0.15 threshold) | ✓ | Comprehensive |

**TABLE 1:** Comparative Evaluation of Existing Methods

## CONCLUSION AND FUTURE WORK

This study presents a robust AI-powered interview assessment system that dynamically generates, evaluates, and adapts interview questions in real time. Through a comprehensive experimental evaluation involving 95 mock interviews and 831 questions, we demonstrated that the proposed system delivers highly accurate and consistent performance, achieving an 82.07% accuracy in score prediction within a ±0.15 margin compared to human evaluators, and maintaining a mean absolute error of 19.74%.

Key advantages of the system include:

1. Real-time adaptivity of questions using semantic feedback loops.
2. High correlation with human scoring, supported by statistical evidence ($r = 0.89$, $\kappa = 0.78$).
3. Detailed and personalized feedback reports, aiding formative learning and performance improvement.
4. Scalability and speed, with rapid generation of both questions and evaluation feedback.

While the system demonstrates strong performance, the following areas require future investigation:

1. **Domain Generalization:** Current evaluation is limited to technical and behavioral interview domains.
2. **Bias Evaluation:** Ongoing work includes ensuring fairness across gender, accent, and language proficiency.
3. **Longitudinal Feedback Effectiveness:** Further user studies are planned to measure how repeated use of the system influences long-term candidate improvement.

## REFRENCES

[1] Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. arXiv. https://doi.org/10.48550/arXiv.1810.04805

[2] Jagadamba, G., Ramesh, S., & Patel, A. (2022). Automated Evaluation of Subjective Answers in Online Examinations. IJERT, 11(5), 324–329. https://doi.org/10.17577/IJERTV11IS050198

[3] Raffel, C., Shazeer, N., Roberts, A., et al. (2020). Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. Journal of Machine Learning Research, 21(140), 1–67. https://www.jmlr.org/papers/volume21/20-074/20-074.pdf
[4] Amidei, J., Piwek, P., & Willis, A. (2020). A Survey on Evaluation Methods for Automatic Question Generation. COLING 2020. https://doi.org/10.18653/v1/2020.coling-main.341
[5] Prabhu, D., & Sharma, M. (2022). AI-Based Question Paper Generator Using Deep Learning. Procedia Computer Science, 210, 423–429. https://doi.org/10.1016/j.procs.2022.02.080
[6] Nayudu, P., & Sharma, P. (2023). AI-Driven Grading in Open-Ended Examinations Using BERT and Similarity Measures. IEEE Transactions on Learning Technologies. https://doi.org/10.1109/TLT.2023.3245678
[7] Bashir, S., Khan, A., & Ahmed, R. (2021). A Machine Learning-Based Subjective Answer Scoring System Using Word Mover's Distance. Computers & Education, 168, 104195. https://doi.org/10.1016/j.compedu.2021.104195
[8] Mulla, N., Patil, S., & Iyer, R. (2022). Dynamic Question Generator for Assessment Using NLP. Springer AISC, Vol. 1362. https://doi.org/10.1007/978-3-030-73050-5_21
[9] Pandey, R., Srivastava, A., & Dubey, A. (2023). BERT-Enabled Interview Automation System for Technical Evaluation. ACM TIST. https://doi.org/10.1145/3601119
[10]Thotad, P., & Kulkarni, S. (2022). Multi-Phase Question Generation Using Deep Learning. Procedia CS, 199, 765–772. https://doi.org/10.1016/j.procs.2022.01.093
[11] Das, B., Sengupta, S., & Roy, A. (2022). Question Generation and Answer Evaluation in Educational Systems. Lecture Notes in Computer Science. https://doi.org/10.1007/978-3-030-93435-4_14
[12]Qin, L., Liang, Y., & Ren, X. (2023). Skill-Based Interview Question Generation Using DuerQues Models. AAAI, 37(9), 11123–11130. https://doi.org/10.1609/aaai.v37i9.27118
[13]Rao, P. S. B., & Sharma, V. (2023). FollowQG: Contextual Interview Bot with Dynamic Follow-Up Questions. AI & Society. https://doi.org/10.1007/s00146-023-01587-4
[14]Zhang, H., Qiu, L., & Sun, J. (2022). Natural Language Understanding in Interview Systems: Current Trends and Future Directions. Artificial Intelligence Review. https://doi.org/10.1007/s10462-022-10108-w
[15]Yakkundi, S., Kulkarni, R., & Ramesh, K. (2023). Intelligent Chatbot for Interview Readiness Training. Journal of Artificial Intelligence Research. https://doi.org/10.1613/jair.1.14018
[16]Kosti, R., Alvarez, J. M., Recasens, A., & Lapedriza, A. (2019). Context Based Emotion Recognition using EMOTIC Dataset. IEEE Transactions on Pattern Analysis and Machine Intelligence, 42(11), 2755–2766. https://doi.org/10.1109/TPAMI.2019.2898298
[17]Li, X., Tao, J., & Kang, Y. (2021). Affective Computing for Interview Readiness: Combining Audio, Text, and Visual Modalities. ACM Transactions on Multimedia Computing, Communications, and Applications, 17(3), 78. https://doi.org/10.1145/3447680
[18]Silver, D., Huang, A., Maddison, C. J., et al. (2016). Mastering the Game of Go with Deep Neural Networks and Tree Search. Nature, 529(7587), 484–489. https://doi.org/10.1038/nature16961
[19]Kumar, A., Sharma, R., & Gupta, N. (2023). AI-Powered Platforms for Interview Preparation: A Review of Capabilities and Challenges. IEEE Access, 11,40215–40229. https://doi.org/10.1109/ACCESS.2023.3267555