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A Systematic Review of AI-Driven Interviewing Systems for Technical and Professional Skills

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Abstract

This systematic review examines AI-driven job interview systems, focusing on their technological foundations, skill coverage, and interaction modalities. Existing platforms span rule-based, AI-enhanced, immersive, and gamified approaches. Advances in natural language processing (NLP), large language models (LLMs), and immersive avatars have enhanced adaptivity and realism, particularly through virtual reality (VR) and augmented reality (AR) simulations. However, most systems remain fragmented, offering limited integration of technical and behavioral assessments, emotional responsiveness, and pedagogical scaffolding. While skill coverage ranges from coding and problem-solving to communication and behavioral readiness, personalization, plagiarism detection, and curriculum alignment are underdeveloped. To advance the field, we propose unified frameworks that combine coding and behavioral training, emotionally adaptive avatars, learner-centered dashboards, and standardized benchmarks. By mapping technological progress and pedagogical limitations, this review establishes a foundation for the next generation of intelligent, inclusive, and context-aware interview preparation systems. To our knowledge, it is the first review to integrate technical, behavioral, and immersive dimensions.

Keywords: Job interview systems, soft skills, coding interviews, AI in education, avatar-based training, virtual reality

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1. INTRODUCTION

This paper provides a systematic review of the existing job interview systems. Interviewing is a critical competency across diverse domains including technical (Qin et al., 2019), engineering (Senthilkumar et al., 2025), business (Takeuchi & Koda, 2021), healthcare (Lee et al., 2020), education (Geng et al., 2024), and law (Hassan et al., 2023). Employers now expect proficiency not only in domain expertise but also in soft skills such as communication, collaboration, and critical thinking. Yet, formal training remains minimal, with existing programs often costly and accessible primarily to affluent individuals (Nofal et al., 2025). This inequity has driven interest in intelligent and automated systems capable of replicating interviews and providing personalized feedback.

Recent advancements in artificial intelligence and virtual reality (VR) have facilitated the creation of robust interview training systems designed to simulate real interview scenarios. These systems take diverse forms, like AI-powered chatbots (Røed et al., 2023) that engage people in simulated interviews, embodied virtual interviewer avatars sometimes within immersive VR settings (Hassan et al., 2023), and mixed-reality simulations. Chou et al. (2022) typically utilize adaptive feedback such as real-time analysis of a candidate's responses, nonverbal cues, or coding solutions to facilitate user improvement. Significantly, these systems encompass various fields. Virtual interview tutors have been developed for commercial and technical job interviews, medical and healthcare training, such as practicing patient interviews (Rädel-Ablass et al., 2025), legal and law enforcement situations, and soft skill management (Luo et al., 2024). Moreover, as the global employment landscape grows more competitive, there is an urgent necessity to create inclusive, accessible, and efficient strategies for interview preparation and evaluation, allowing candidates from varied backgrounds, including individuals with disabilities or anxiety disorders, to effectively demonstrate their competencies.

Traditional academic assessments such as written exams, multiple-choice tests, and project-based coursework often emphasize theoretical knowledge or technical problem-solving in controlled settings. While effective for measuring content mastery, these forms of evaluation rarely capture the interactive, adaptive, and high-pressure dynamics of job interviews. Similarly, offerings from career development offices, though valuable, are typically optional and resource-limited, prompting the rise of digital platforms for interview preparation. However, these interviewing systems vary greatly in design and focus, with many limited to either technical or behavioral training. A comprehensive understanding of their effectiveness and limitations remains lacking, and few offer personalized, adaptive, or realistic feedback, leaving key aspects of professional readiness under addressed.

This review is motivated by the need to identify what has been achieved, what limitations persist, and how future systems can better support the transition from academic to professional environments. It is guided by five research questions (RQ1–RQ5) concerning technologies, pedagogical strategies, real-world alignment, professional skill support, existing gaps, and technical, pedagogical, and ethical challenges. By consolidating prior work, this study highlights critical gaps including absent integration of technical and behavioral assessments, limited emotional adaptivity, inadequate coding simulations with plagiarism detection, and insufficient personalization and outlines directions for future research.

The rest of the paper is organized as follows: Section 2 outlines the methodology for literature selection and analysis. Section 3 reviews and categorizes existing job interview systems outlining key future research directions. Section 4 analyzes findings based on the research questions. Finally, Section 5 concludes by summarizing the key insights.

ISSN: 2473-4901
v11 n6438

2. METHODOLOGY

To ensure rigor and transparency, this review adopts a structured methodology comprising three components: the search strategy (scope and reproducibility), the inclusion and exclusion criteria (quality boundaries), and the selection process (multi-stage screening).

A. Database and Search Strategy
A comprehensive keyword search strategy was designed to identify the most relevant and recent studies for this review. It focused on system types, embodied interaction (e.g., avatars), assessed skills (e.g., soft and technical), interaction modalities (e.g., AR/VR), and feedback mechanisms. A structured query was applied across academic databases to capture high-quality studies, with priority given to peer-reviewed publications and selective inclusion of preprints when they addressed recent advances aligned with the review objectives with potential contributions for their relevancy.

Sample Keywords

Category	**Keywords**
System Type	"Intelligent job interview system" OR "interviewing system" OR "mock interview system"
Agents	"Avatar" OR "Virtual agent"
Skills Assessed	"Soft skills" OR "Communication"
Interview Types	"Job interview" OR "Mock interview" OR "Coding interview" OR "Soft skill interview"
Feedback Mechanism	"Personalized feedback" OR "Adaptive feedback"
Immersive Technology	"AR" OR "Augmented Reality" OR "VR" OR "Virtual Reality"
Skills Emphasis	"Communication" OR "Soft skills" OR "Coding skill" OR "Technical skill"

B. Inclusion and Exclusion Criteria
The inclusion criteria were designed to prioritize peer-reviewed research studies relevant to the development of Job Interview systems. However, high-quality preprints and early-stage publications were also considered when they contributed substantially to emerging trends or recent technological advancements. These were critically appraised for relevance and quality before inclusion. We included studies that:

(1) Presented or evaluated Job Interview platforms.
(2) Presented or evaluated Job Interview platforms focusing on Augmented Reality, Virtual Reality, and Gamification.
(3) Integrated avatar-based or embodied conversational agents.
(4) Offered mock coding interviews or simulated roleplay interactions.
(5) Provided personalized or adaptive feedback mechanisms and studies were excluded if they:
(a) Not written in English.
(b) Focused solely on general e-learning.

C. Selection Process
The literature selection process followed a systematic four-stage PRISMA approach (Mutter et al., 2021), as illustrated in the flowchart (Figure 1).

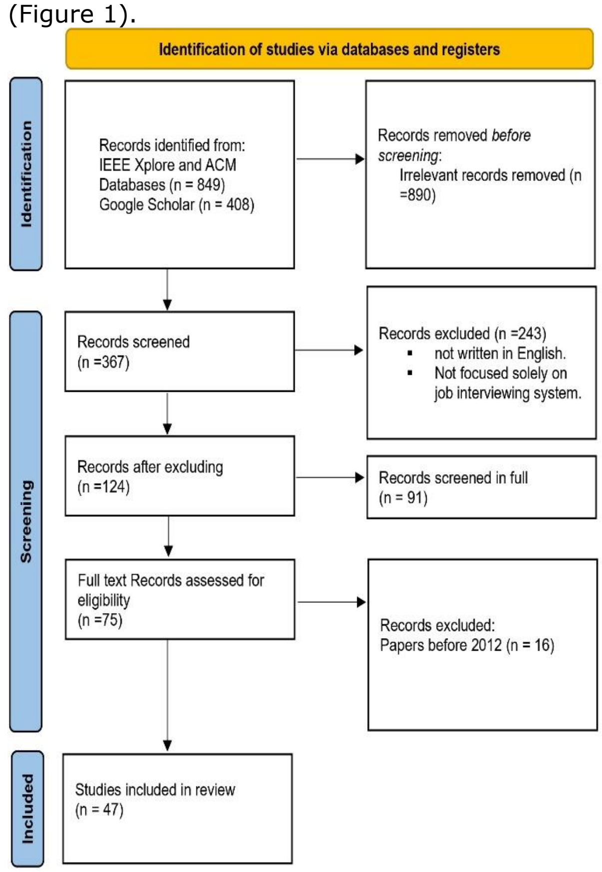

Figure 1: Paper Selection Process

Identification Phase: An initial pool of 1257 records were retrieved through comprehensive database searches across IEEE Xplore and ACM Digital Library (n = 849) and Google Scholar (n = 408) using a predefined set of related keywords as specified before. Prior to formal screening, 890

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v11 n6438

records were excluded for irrelevance based on manual inspection of titles and abstracts. This review relies on IEEE Xplore, ACM Digital Library, and Google Scholar as primary databases. While this ensured strong coverage of computing and AI-focused publications, the exclusion of broader indexing services such as Scopus and Web of Science may have omitted some interdisciplinary studies. However, the inclusion of Google Scholar helped mitigate this limitation by retrieving relevant works.

Screening Phase: A total of 367 articles were subjected to title and abstract screening. Of these, 243 records were excluded for failing to meet the inclusion criteria. This resulted in 124 potentially relevant records progressing to the next stage.

Eligibility Assessment: Full texts of 91 studies were reviewed in detail to determine their suitability for inclusion. At this stage, an additional 16 papers were excluded due to being published prior to 2012, as they did not reflect the recent advances in AI, natural language processing, and immersive technologies that underpin modern interview systems. The remaining 75 studies were evaluated against the full inclusion criteria. This threshold ensured that it included works aligned with the technological advancements most relevant to current and future interview training systems.

Inclusion Phase: Following a rigorous assessment, 44 studies were determined to meet all predefined inclusion criteria and were selected for detailed analysis in this systematic review. This assessment went beyond basic inclusion criteria and considered factors such as methodological soundness (clarity of design, evaluation approach), technological relevance (use of AI, VR/AR, or feedback mechanisms), and contribution to the research questions. Preprints were included only if they demonstrated clear methodological transparency and novel contributions.

3. REVIEW OF INTERVIEW TRAINING SYSTEMS

This review first categorizes interview training systems by (1) "Technological Approaches
(2) "Skills Assessed", and (3) "Modality".

A high-level taxonomy of AI-enhanced interview systems in Figure 2. This diagram summarizes how existing systems are categorized and where research gaps emerge. It provides a taxonomy of AI-enhanced job interview systems across five dimensions: technologies, skills, modalities, challenges, and future directions. It identifies four main technological approaches rule-based, AI-driven (NLP/LLMs), immersive VR/AR, and gamification which were used to assess soft, technical, and behavioral skills. Here, interaction modalities include text-based, audio-visual, and immersive environments.

Key challenges include limited real-time emotional feedback, skill-specific system silos, and accessibility issues in VR. Future directions emphasize the need for integrated platforms,

emotionally adaptive avatars, plagiarism detection, culturally inclusive interfaces, and large-scale evaluations with standardized benchmarks

A. Technological Approaches

i. Rule-based Systems: Early efforts in virtual interview training often relied on rule-based or scripted approaches. Rule-based systems employ scripted dialogue and decision trees to ensure predictable interactions. Early examples include ERICA, which used keyword detection for follow-up questions but lacked adaptability (Kawahara et al., 2021), and semi-automated multi-agent interviewing with partial ML support (Kawai et al., 2022). Other efforts applied rule-based templates with NLP for question generation (Pandey et al., 2023), conversational chatbots with state-transition models (Boudjani et al., 2023), finite state machines for social cue detection (Baur et al., 2013), and hybrid Theory of Mind models (Belkaid et al., 2014). These systems provide structure but remain rigid, non-adaptive, and limited in scalability.

ii. Intelligent Systems (AI-driven): The advent of Artificial Intelligence (AI) has significantly reshaped job interview preparation, enabling systems that integrate natural language processing (NLP), computer vision, and large language models (LLMs) for dynamic evaluation. Early platforms such as Big Interview (Fulk et al., 2022) and NexInterview (S et al., 2025) illustrate how NLP and generative AI can support structured mock interviews. Building on these foundations, systems like CIRVR (Adiani et al., 2022) and ITEM (Nofal et al., 2025) incorporate virtual reality and real-time feedback to deliver personalized, adaptive training.

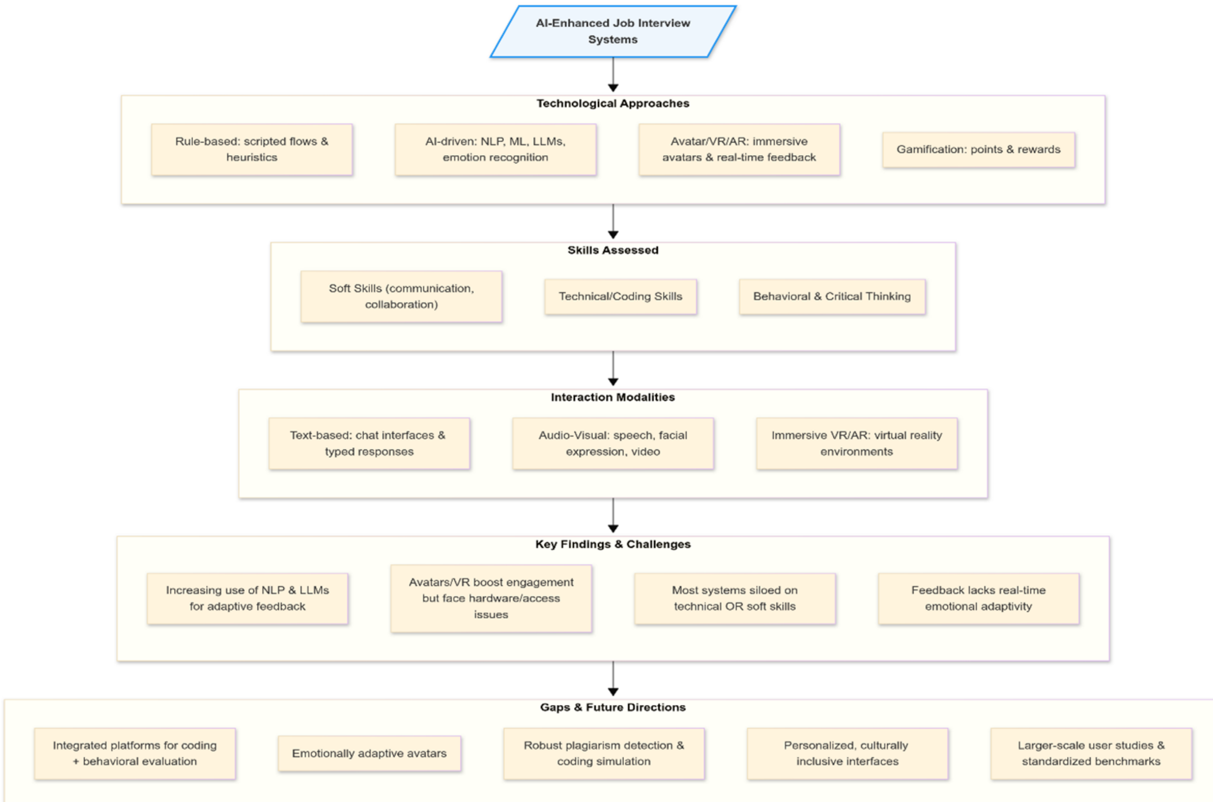

Figure 2: Overview of AI-Enhanced Job Interview Systems: Taxonomy and Future Directions

A central trend is the shift from static, rule-based approaches to adaptive agents powered by LLMs and multimodal cues. For example, GPT-4o has been applied in technical interviews with high realism (Gomez et al., 2025), yet these implementations often neglect emotion awareness and plagiarism detection. Similarly, Gemini-based adaptive questioning (Rai, 2025) advances interactivity but lacks affective sensing.

Fairness and transparency have also emerged as critical concerns. Pathak et al. (2024) demonstrate that asynchronous, LLM-driven video interviews can enhance demographic fairness, though delayed feedback and reliance on a single modality limit effectiveness. Complementary approaches integrate inclusivity tools such as gaze-tracking in VR (Adjani et al., 2022), yet hardware demands and limited feedback remain barriers. Likewise, video simulation with analytics has supported language training (Jarvis et al., 2024), though it remains domain-specific. Nofal et al. (2025) further combine VR, LLMs, and bias-testing frameworks to create bias-aware practice, though fidelity is constrained by the absence of gaze or head tracking.

Expanding beyond evaluation, several systems employ predictive and multimodal models. NLP–CNN pipelines have been explored for soft-skill and personality prediction, albeit with generic feedback (Rao et al., 2025). Voice-first, role-specific simulations extend Gemini applications (S et al., 2025), yet real-time analytics and expressiveness are limited. Other innovations include vision–speech fusion for emotion recognition (Golande et al., 2025), graph-based skill-targeted questioning (Qin et al., 2024), and speaker-willingness recognition for adaptive questioning (Nagasawa et al., 2023), though each faces constraints in validation, flexibility, or scope.

Collectively, these systems affirm the potential of AI to enhance confidence, self-assessment, and accessibility. However, persistent limitations including limited personalization, underdeveloped affective sensing, and the absence of standardized benchmarking underscore the need

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v11 n6438

for larger-scale evaluations and rigorous validation.

iii. Avatar-based / Immersive VR/AR-based Systems: AI-powered interview simulators are increasingly adopting avatars and extended reality to deliver immersive and interactive experiences. By moving beyond static interfaces and text-based exchanges, these systems aim to provide dynamic, lifelike simulations that enhance user engagement and skill transfer (Nofal et al., 2025; Sahani et al., 2025).

To illustrate, Nofal et al. (2025) introduced a VR-based platform built with Oculus Quest and Unity, where animated avatars and ChatGPT-generated questions were used to assess communication, leadership, and domain knowledge through sentiment-driven scoring and bias analysis. Although the system proved effective in controlled studies, it remains constrained by its dependence on high-end hardware, the absence of gaze tracking, and the lack of large-scale validation. Building on this trajectory, Sahani et al. (2025) presented a scalable web-based platform with a 3D avatar created using React.js and Three.js. While it demonstrated high question accuracy (~95%), robust speech-to-text performance (>90%), and measurable gains in user confidence (80%), its limited realism, absence of multilingual capacity, and lack of expert-curated content reduce its applicability in broader contexts.

In parallel, several systems have sought to broaden accessibility. AIVATAR (Bachhav et al., 2023) integrates 3D avatars with aptitude testing and instant textual feedback to reduce interview anxiety in low-stakes practice environments. Yet, despite its promise, the platform remains conceptual, with no empirical validation and limited non-verbal cue integration. Extending this line of research, Hassan et al. (2023) developed a multimodal platform for investigative interviews across VR, desktop, and audio formats. Their findings indicate that VR fosters stronger presence and realism compared to other modalities; however, binary feedback, reliance on proprietary APIs, and synthesized voices limit its utility. Similarly, Røed et al. (2023) used a fine-tuned GPT-3 to simulate conversations with a child avatar, showing that personalized feedback significantly improved questioning strategies skills directly transferable to interview contexts.

At the same time, efforts have also focused on enhancing realism. Ashrafi et al. (2024) employed Unreal Engine, MetaHuman, and Convai to develop avatars across VR, AR, and desktop environments. While the system captures physiological signals to detect anxiety, it still lacks real-time coaching and its AR features remain incomplete. Likewise, Hasan et al. (2023) introduced SAPIEN, a demo platform with emotionally expressive 3D agents powered by LLMs and multilingual speech technologies. Despite its potential for communication training, its short sessions, limited conversational memory, and lack of empirical evaluation restrict practical adoption.

Taken together, these avatar-based and immersive VR/AR systems represent a substantial step toward more realistic, engaging, and personalized interview preparation. Nevertheless, challenges relating to hardware accessibility, comprehensive non-verbal analysis, and limited empirical validation highlight the need for integrated, rigorously tested frameworks before widespread implementation.

iv. Gamification-based Systems: Gamification has emerged as a powerful strategy in the design of modern job interview systems. By incorporating game elements such as points, achievements, interactive simulations, and immersive environments, these systems aim to enhance candidate engagement, reduce interview anxiety, and deliver more meaningful assessments. This review explores recent developments in gamification-based job interview systems, summarizing the technological approaches and key contributions of several published works. Table 1 in Appendix A depicts an overview of gamification-based systems.

The reviewed systems collectively highlight the diverse application of gamification in job interview settings. Some platforms, like the Metahuman-based VR system (Ashrafi et al., 2024) and the agent-based VR training, prioritize immersion and realism to build candidate confidence, while others, like Conversate (Daryanto et al., 2025) and the cognitive assessment tool, integrate adaptive simulations and machine learning to personalize feedback and scoring. Despite the varied approaches, all these systems converge on the goal of making interview preparation more interactive, insightful, and equitable.

B. Skills Assessed

i. Soft Skills: Table 2 in Appendix A below presents a comparative overview of prominent AI-powered systems designed for job interview preparation, with a particular emphasis on soft skills and competency-based assessment. Each system is evaluated across multiple dimensions,

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v11 n6438

including its primary skill focus, underlying AI technologies, input modalities, feedback mechanisms, and notable strengths and limitations. This structured comparison offers insights into how different platforms approach interview readiness through multimodal interaction, adaptive feedback, and targeted soft skill development, while also highlighting existing gaps in non-verbal analysis, empirical validation, and immersive realism.

ii. Technical and Coding Skills: Over the past few years, a growing body of research has explored how AI-based systems can simulate, assess, and enhance technical interviews, particularly for roles requiring coding and problem-solving skills. This review in Table 3 in Appendix A depicts recent academic work on AI-driven interview systems designed for technical and coding roles, summarizing the innovations, methodologies, and implications of each.

The reviewed systems collectively demonstrate how AI enhances technical interviews through adaptive questioning and multimodal evaluation.

iii. Behavioral and Critical Thinking Skills: Some systems extend beyond communication by targeting behavioral readiness and critical thinking. For instance, Conversate, developed by Daryanto et al. (2025), employed dialogic reflection, while STAR-based evaluations (Siswanto et al., 2022) scaffold structured behavioral responses. Adaptive questioning (Nagasawa et al., 2023) and bias-testing frameworks (Nofal et al., 2025) also prompt reasoning beyond surface-level answers. However, explicit support for these skills remains limited compared to technical and soft-skill training.

C. Modality

Text-based and Multimodal Interviewing Systems: The reviewed AI-based job interview systems in Figure 3 were categorized based on their primary interaction modalities: Text-based systems primarily rely on typed input and output, enabling question delivery and response evaluation via chat-like interfaces. Textual systems include Anaza et al. (2023), Ashrafi et al. (2024), Bachhav et al. (2023), Chou et al. (2022), Hasan et al. (2023), Mishra et al. (2024), Namratha et al. (2024), Nofal et al. (2025), Rao et al. (2025), Sahani et al. (2025), Senthilkumar et al. (2025), and Wilkie and Rosendale (2024).

Audio-visual systems integrate spoken input and/or output, often enhancing realism by incorporating speech recognition (e.g., Google STT, DeepSpeech) and text-to-speech (TTS) engines (e.g., Amazon Polly, Google TTS). Audio-based systems have been presented by Anaza et al. (2023), Ashrafi et al. (2024), Bachhav et al. (2023), Chou et al. (2022), Hasan et al. (2023), Namratha et al. (2024), Nofal et al. (2025), Rao et al. (2025), Røed et al. (2023), Sahani et al. (2025), Senthilkumar et al. (2025), Siswanto et al. (2022), and Wilkie and Rosendale (2024).

Visual modalities are represented by Anaza et al. (2023), Ashrafi et al. (2024), Bachhav et al. (2023), Chou et al. (2022), Hasan et al. (2023), Namratha et al. (2024), Nofal et al. (2025), Røed et al. (2023), Sahani et al. (2025), Senthilkumar et al. (2025), and Wilkie and Rosendale (2024).

Text-based platforms are lightweight and scalable but lack non-verbal cue analysis, reducing authenticity. Audio-based systems enhance verbal communication through speech recognition yet remain constrained by weak emotion detection and dependence on reliable STT/TTS. Video-based approaches offer greater realism via facial and gesture recognition but demand high computational resources and raise privacy concerns. Collectively, these modalities reveal a trade-off between accessibility and realism, underscoring the need for integrated multimodal frameworks that combine efficiency with feedback-rich, authentic interaction.

This section focused on text-based and multimodal systems, while immersive VR/AR treated as a distinct modality was discussed earlier under Technological Approaches (Section 3.A.iii).

By synthesizing existing interviewing systems, this systematic review makes significant contributions. Compared to previous reviews that are either technically narrow e.g., Barpute et al. (2024) or ethically focused like Hunkenschroer and Luetge (2022), or have insufficient system diversity and technical depth e.g., Abedi (2022) which lacks breadth in reviewed platforms and ignores cutting-edge LLM/VR-based tools, our review takes a comprehensive approach by integrating the evaluation of both coding and soft skills, feedback mechanisms, and immersive interaction modalities (VR/AR/avatar), reflecting the multidimensional demands of real-world job interviews. Furthermore, our review bridges the gap between educational training and industry expectations, an area largely overlooked by prior surveys.

ISSN: 2473-4901
v11 n6438

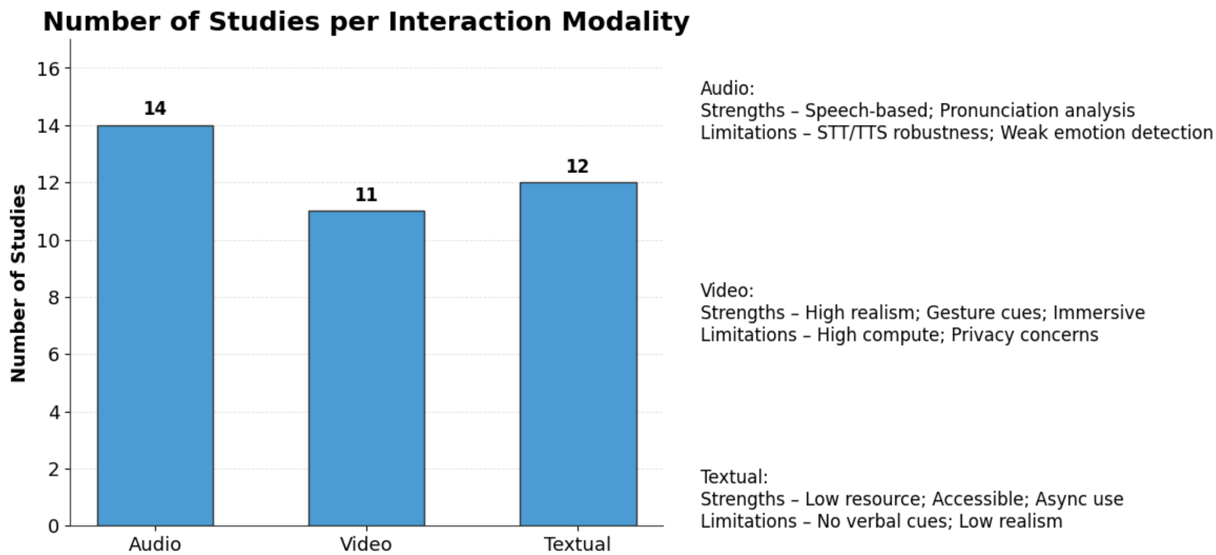

Figure 3: Summary of Job Interview System based on their primary interaction modalities

Notably, in this process the authors discovered several critical research gaps, including the absence of comprehensive systems capable of concurrently evaluating technical coding skills and behavioral competencies, inadequate real-time emotionally adaptive feedback, limitations in avatar-driven interactions, insufficient adaptability to varying professional and user contexts, lack of specialized support for realistic coding interview simulations, insufficient attention to plagiarism detection and limited personalized interviewing experiences. This paper identifies several key future research directions essential for advancing interview preparation systems. Specifically, progress should focus on:

- Integrating technical and behavioral assessments, enabling holistic evaluations that capture both domain expertise and interpersonal competencies.
- Enhancing avatar realism and emotional responsiveness, thereby fostering more authentic and immersive candidate–interviewer interactions.
- Providing real-time adaptive feedback, ensuring that learners receive personalized guidance aligned with their evolving performance.
- Developing robust coding simulations with plagiarism detection, to uphold integrity and rigor in technical skill assessment.
- Designing authentic, participatory mock interviews, mirroring real-world hiring practices and supporting experiential learning.

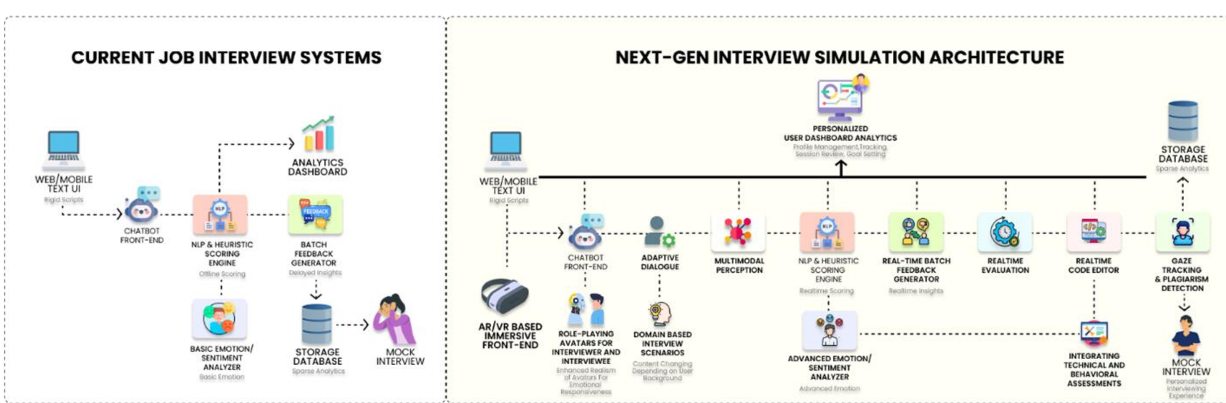

Figure 4: Architectural trajectory of AI-driven interview systems

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v11 n6438

Collectively, these directions guide the development of intelligent, inclusive platforms that replicate real-world interview complexity while enhancing candidate readiness through personalized and adaptive training. The prospective architecture transformation in AI-Driven Interview Systems from the present context is illustrated in Figure 4. Here, this figure 4 illustrates the evolution from conventional job interview systems to proposed next-generation AI-driven interview simulation architecture. The left side depicts current systems that primarily rely on web/mobile text-based user interfaces and chatbot front ends powered by offline NLP and heuristic scoring. These systems often provide delayed batch feedback, rely on basic sentiment analysis, and support only limited user analytics and mock interview functionality. In contrast, the right side presents a next-generation architecture that integrates AR/VR-based immersive interfaces, emotionally responsive role-playing avatars, domain-based adaptive dialogue, and multimodal perception. Real-time scoring, evaluation, and feedback are supported by advanced NLP models and sentiment analyzers. Technical assessments are conducted through an embedded real-time code editor with integrated gaze tracking and plagiarism detection. A personalized user dashboard enables analytics-driven session review, goal tracking, and profile management. Collectively, these enhancements enable more engaging, adaptive, and realistic interview simulations that holistically assess both technical and behavioral competencies.

4. ANALYSES OF RESEARCH QUESTIONS

A. RQ1: What are the key features, technologies, and pedagogical strategies employed in existing job interviewing systems?

Section 3 outlines the technological evolution of job interview systems, classifying them into four primary categories: rule-based, AI-driven, avatar-based/immersive, and gamification-enhanced platforms. Rule-based systems rely on scripted logic and predefined keyword triggers, offering reliable and consistent interactions but lacking adaptability and personalization. In contrast, AI-driven systems leverage advanced techniques such as natural language processing, computer vision, and LLMs to enable real-time, multimodal evaluation. These platforms provide detailed, context-aware feedback on candidate performance, encompassing verbal, nonverbal, and emotional dimensions, thereby supporting a more comprehensive assessment of interview readiness.

Each category offers distinct affordances but exhibit varied levels of pedagogical integration. Rule-based systems align with behaviorist pedagogy, emphasizing scripted interactions and fixed feedback, though they lack adaptability and depth. Intelligent systems employing NLP and LLMs enable dynamic, real-time feedback aligned with formative and adaptive learning principles, but few consistently incorporate structured pedagogical scaffolding. Immersive platforms support experiential learning through realistic simulations, reflecting constructivist ideals; however, they often neglect structured reflection and personalized guidance. Gamified systems enhance engagement but typically lack instructional depth, with feedback and learning pathways remaining underdeveloped.

So, technically robust but pedagogically limited, these systems require adaptive, learner-centered strategies to enable effective and transferable learning.

B. RQ2: To what extent do existing job interview systems in the computing field bridge the gap between academic training and real-world hiring expectations?

The review finds a moderate alignment between job interview systems and real-world expectations. Some systems offer realistic whiteboard style coding simulations and behavioral analysis, bridging academic exercises with practical hiring practices. However, a significant portion of platforms still focus narrowly on either behavioral or technical aspects, failing to present the integrative complexity of actual job interviews.

A few systems have made strides toward realism and engagement and integrate dialogic feedback and transcript annotation, encouraging reflective learning aligned with real-world communication tasks. Nonetheless, many reviewed systems lack authentic, industry-driven evaluation models and employer-aligned performance metrics.

C. RQ3 How do these systems support different aspects of professional development, including communication skills, critical thinking, and behavioral readiness?

Soft skills development is increasingly embedded in intelligent and immersive systems. AI-enhanced platforms like *SAPIEN* and *InterviewPal* incorporate sentiment analysis, speech modulation, and facial emotion recognition to

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v11 n6438

deliver multimodal feedback (Hasan et al., 2023; Namratha et al., 2024). This allows candidates to reflect not only on what they say, but also how they say it, a key component of behavioral readiness.

Critical thinking is indirectly supported through scenario-based questioning, adaptive follow-up prompts, and STAR model-based evaluations. Yet, explicit support for reflective learning and metacognitive feedback is present in only a few systems (e.g., *Conversate*), indicating an underexplored opportunity for systems to scaffold users' self-regulated learning processes (Daryanto et al., 2025).

Overall, systems integrating emotion-aware AI and adaptive feedback mechanisms are more likely to foster deep skill development and sustained user engagement.

D. RQ4: What gaps exist in the current systems that future research must address to build intelligent, context-aware, and career-aligned interview preparation platforms?

Our analysis highlights several underexplored directions in the development of job interview simulation systems. Notably, there is a lack of platforms that integrate mock coding and behavioral interviews in a unified environment, despite the prevalence of hybrid formats in real-world hiring processes particularly for computing students. Furthermore, current systems show limited alignment with computing education, missing opportunities to embed interview training into curriculum-relevant activities like code reviews or plagiarism detection.

Avatars, while increasingly present, are often underutilized for soft skill development due to limited emotional expressiveness, adaptability, and feedback capabilities. Similarly, real-time coding environments remain largely neglected, with most systems offering asynchronous or non-interactive assessments that fail to simulate live technical interviews. Emotional adaptivity in feedback is also rare; while multimodal sensing (e.g., voice, facial cues) is becoming more common, only a few systems leverage this input for dynamic, personalized responses. Finally, content adaptation based on user interest or performance history is generally absent, reducing the relevance and long-term engagement of these systems. These gaps present valuable opportunities for future research and innovation.

E. RQ5: What are the major challenges and limitations (technical, pedagogical, ethical) faced by these systems in achieving sustained learning impact and user trust?

From a technical perspective, many systems face challenges such as latency in real-time multimodal processing, limited scalability, and unstable integration across core components, including speech-to-text, natural language processing, and computer vision. Pedagogically, feedback mechanisms are often generic, lacking the granularity and adaptability required for personalized learning paths or formative assessment. Ethically, major concerns persist around potential privacy risks associated with the collection of sensitive multimodal user data. Together, these challenges hinder the effectiveness, fairness, and trustworthiness of current systems, posing significant barriers to their widespread adoption and long-term impact in educational and professional settings.

5. CONCLUSION

This article presented a systematic review of AI-driven interview systems, synthesizing research across four technological approaches- rule-based, intelligent, avatar-based immersive, and gamification. By examining assessed skills and interaction modalities, the review provided a holistic account of how current systems simulate interviews, deliver feedback, and support professional skill development. A central contribution of this work is its integration of technical and behavioral perspectives, which prior reviews have largely treated in isolation. In doing so, the study establishes a comprehensive foundation for aligning interview preparation platforms with both academic training and employer expectations. This review is the first to systematically integrate technical, behavioral, and immersive perspectives in interview systems.

The analysis demonstrates that while advances in NLP, LLMs, and immersive VR/AR have enhanced realism and adaptivity, the field remains fragmented. Persistent challenges include limited personalization, insufficient affective and multimodal feedback, scarce empirical validation, and the absence of standardized benchmarks. For Information Systems and Computer Information Systems education, these findings highlight both the potential and the current shortcomings of leveraging intelligent simulations to foster career readiness. Looking ahead, future systems should embed real-time coding environments within avatar-based simulations, incorporate plagiarism-aware technical assessments, and utilize affective computing for emotionally adaptive feedback. Equally important are culturally inclusive, multilingual designs and

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v11 n6438

rigorous benchmarking frameworks to ensure fairness and transparency. By synthesizing the existing literature, identifying critical gaps, and outlining research directions, this review establishes a roadmap for the next generation of intelligent, inclusive, and context-aware interview preparation systems. Such systems are essential for bridging the gap between academic preparation and professional hiring demands in an increasingly competitive global employment landscape.

6. REFERENCES

Adiani, D., Itzkovitz, A., Bian, D., Katz, H., Breen, M., Hunt, S., … & Sarkar, N. (2022). Career interview readiness in virtual reality (CIRVR): A platform for simulated interview training for autistic individuals and their employers. ACM Transactions on Accessible Computing (TACCESS), 15(1), 1–28. https://doi.org/10.1145/3505560

Anaza, E., Mabrey, P., Sato, M., Miller, O., & Thompson, J. (2023). Improving student interview preparation through collaborative multimodal mock-interview assignments. Sport Management Education Journal, 17(2), 164–176. https://doi.org/10.1123/smej.2021-0021

Ashrafi, N., Vona, F., Ringsdorf, C., Hertel, C., Toni, L., Kailer, S., … & Voigt-Antons, J. N. (2024, October). Enhancing job interview preparation through immersive experiences using photorealistic, AI-powered Metahuman avatars. In 2024 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct) (pp. 345–346). IEEE. https://doi.org/10.1109/ISMAR-Adjunct64951.2024.00083

Bachhav, P. K., Khandale, O. S., & Karnavat, S. R. (2023, November). AIVATAR: Scrutinizing interview readiness platform with intelligent assessment and aptitude. International Research Journal of Modernization in Engineering Technology and Science, 5(11), 1900–1903. https://www.irjmets.com/uploadedfiles/paper//issue_11_november_2023/46469/final/fin_irjmets1700472402.pdf

Barpute, J. V., Wattamwar, O., Pakjade, S., & Diwate, S. (2024, December). A survey of AI-driven mock interviews using GenAI and machine learning (InterviewX). In 2024 4th International Conference on Ubiquitous Computing and Intelligent Information Systems (ICUIS) (pp. 217–224). IEEE. https://doi.org/10.1109/ICUIS64676.2024.10866631

Abedi, M. (2022). Towards a reference architecture of AI-based job interview systems. Ecole Polytechnique de Montréal. https://publications.polymtl.ca/10215/

Baur, T., Damian, I., Gebhard, P., Porayska-Pomsta, K., & André, E. (2013, September). A job interview simulation: Social cue-based interaction with a virtual character. In 2013 International Conference on Social Computing (pp. 220–227). IEEE. https://doi.org/10.1109/SocialCom.2013.39

Belkaid, M., & Sabouret, N. (2014). A logical model of theory of mind for virtual agents in the context of job interview simulation. arXiv preprint arXiv:1402.5043. https://doi.org/10.48550/arXiv.1402.5043

Boudjani, N., Colas, V., Joubert, C., & Amor, D. B. (2023, May). AI chatbot for a job interview. In 2023 46th MIPRO ICT and Electronics Convention (MIPRO) (pp. 1155–1160). IEEE. https://doi.org/10.23919/MIPRO57284.2023.10159831

Chou, Y. C., Wongso, F. R., Chao, C. Y., & Yu, H. Y. (2022, April). An AI mock-interview platform for interview performance analysis. In 2022 10th International Conference on Information and Education Technology (ICIET) (pp. 37–41). IEEE. https://doi.org/10.1109/ICIET54416.2022.9753837

Daryanto, T., Ding, X., Wilhelm, L. T., Stil, S., Knutsen, K. M., & Rho, E. H. (2025). Conversate: Supporting reflective learning in interview practice through interactive simulation and dialogic feedback. Proceedings of the ACM on Human-Computer Interaction, 9(1), 1–32. https://doi.org/10.1145/3701188

Dascalescu, S., Dumitran, A. M., & Vasiluta, M. A. (2025). Leveraging generative AI for enhancing automated assessment in programming education contests. arXiv preprint arXiv:2506.05990. https://doi.org/10.48550/arXiv.2506.05990

Dougherty, Q., & Mehta, R. (2025, May). Proving the coding interview: A benchmark for formally verified code generation. In 2025 IEEE/ACM International Workshop on Large

ISSN: 2473-4901
v11 n6438

Language Models for Code (LLM4Code) (pp. 72–79). IEEE. https://doi.org/10.1109/LLM4Code66737.2025.00014

Fulk, H. K., Dent, H. L., Kapakos, W. A., & White, B. J. (2022). Doing more with less: Using AI-based Big Interview to combine exam preparation and interview practice. Issues in Information Systems, 23(4), 118–127. https://doi.org/10.48009/4_iis_2022_118

Geng, W., Zhou, C., & Bian, Y. (2024). Change gently: An agent-based virtual interview training for college students with great shyness. Virtual Reality, 29(1), 12. https://doi.org/10.1007/s10055-024-01076-y

Gomez, N., Batham, S. S., Volonte, M., & Do, T. D. (2025). Virtual interviewers, real results: Exploring AI-driven mock technical interviews on student readiness and confidence. arXiv preprint arXiv:2506.16542. https://doi.org/10.48550/arXiv.2506.16542

Hasan, M., Ozel, C., Potter, S., & Hoque, E. (2023, September). SAPIEN: Affective virtual agents powered by large language models. In 2023 11th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW) (pp. 1–3). IEEE. https://doi.org/10.1109/ACIIW59127.2023.10388188

Hassan, S. Z., Sabet, S. S., Riegler, M. A., Baugerud, G. A., Ko, H., Salehi, P., … & Halvorsen, P. (2023). Enhancing investigative interview training using a child avatar system: A comparative study of interactive environments. Scientific Reports, 13(1), 20403. https://doi.org/10.1038/s41598-023-47368-2

Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of AI-enabled recruiting and selection: A review and research agenda. Journal of Business Ethics, 178(4), 977–1007. https://doi.org/10.1007/s10551-022-05049-6

Jarvis, A., Ho, A., & Lim, G. (2024). Impressing artificial intelligence: Automated job interview training in professional English subjects. RELC Journal. Advance online publication. https://doi.org/10.1177/00336882241245449

Kawahara, T., Inoue, K., & Lala, D. (2021). Intelligent conversational android ERICA applied to attentive listening and job interview. arXiv preprint arXiv:2105.00403. https://doi.org/10.48550/arXiv.2105.00403

Kawai, H., Muraki, Y., Yamamoto, K., Lala, D., Inoue, K., & Kawahara, T. (2022, September). Simultaneous job interview system using multiple semi-autonomous agents. In Proceedings of the 23rd Annual Meeting of the Special Interest Group on Discourse and Dialogue (SIGDIAL) (pp. 107–110). ACL. https://doi.org/10.18653/v1/2022.sigdial-1.12

Lee, J., Kim, H., Kim, K. H., Jung, D., Jowsey, T., & Webster, C. S. (2020). Effective virtual patient simulators for medical communication training: A systematic review. Medical Education, 54(9), 786–795. https://doi.org/10.1111/medu.14152

Leutner, F., Codreanu, S. C., Brink, S., & Bitsakis, T. (2023). Game-based assessments of cognitive ability in recruitment: Validity, fairness and test-taking experience. Frontiers in Psychology, 13, 942662. https://doi.org/10.3389/fpsyg.2022.942662

Luo, X., Wang, Y., Lee, L. H., Xing, Z., Jin, S., Dong, B., … & Hui, P. (2024). Using a virtual reality interview simulator to explore factors influencing people’s behavior. Virtual Reality, 28(1), 56. https://doi.org/10.1007/s10055-023-00934-5

Mishra, P. K., Arulappan, A. K., Ra, I. H., Rose, G., & Lee, Y. S. (2024, November). AI-driven virtual mock interview development. In 2024 Joint 13th International Conference on Soft Computing and Intelligent Systems and 25th International Symposium on Advanced Intelligent Systems (SCIS & ISIS) (pp. 1–4). IEEE. https://doi.org/10.1109/SCISISIS61014.2024.10760210

Mutter, B. A., Tetzlaff, J., Moher, D., & Altman, D. G. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71

Nagasawa, F., Okada, S., Ishihara, T., & Nitta, K. (2023). Adaptive interview strategy based on interviewees’ speaking willingness

ISSN: 2473-4901
v11 n6438

recognition for interview robots. IEEE Transactions on Affective Computing. Advance online publication. https://doi.org/10.1109/TAFFC.2023.3309640

Namratha, M., Lokesh, R., Bhat, P., Srikanth, N., & Gagan, M. (2024, April). InterviewPal—Elevating interview automation with deep learning and natural language processing perspectives. In 2024 International Conference on Emerging Technologies in Computer Science for Interdisciplinary Applications (ICETCS) (pp. 1–6). IEEE. https://doi.org/10.1109/ICETCS61022.2024.10543368

Nofal, A. B., Ali, H., Hadi, M., Ahmad, A., Qayyum, A., Johri, A., … & Qadir, J. (2025). AI-enhanced interview simulation in the metaverse: Transforming professional skills training through VR and generative conversational AI. Computers and Education: Artificial Intelligence, 8, 100347. https://doi.org/10.1016/j.caeai.2024.100347

Pandey, R., Chaudhari, D., Bhawani, S., Pawar, O., & Barve, S. (2023, March). Interview bot with automatic question generation and answer evaluation. In 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS) (Vol. 1, pp. 1279–1286). IEEE. https://doi.org/10.1109/ICACCS57279.2023.10112918

Pathak, G. (2024, June). Asynchronous AI interviews for technical roles: Improving candidate experience and reducing interview fatigue. International Journal of Novel Research and Development, 9(6), f140–f149. http://ijnrd.org/papers/IJNRD2406504.pdf

Qin, C., Zhu, H., Shen, D., Sun, Y., Yao, K., Wang, P., & Xiong, H. (2023). Automatic skill-oriented question generation and recommendation for intelligent job interviews. ACM Transactions on Information Systems, 42(1), 1–32. https://doi.org/10.1145/3604552

Qin, C., Zhu, H., Zhu, C., Xu, T., Zhuang, F., Ma, C., … & Xiong, H. (2019, July). DuerQuiz: A personalized question recommender system for intelligent job interview. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (pp. 2165–2173). ACM. https://doi.org/10.1145/3292500.3330706

Prajwal, R., Divya, D., Gowda, H. K., & Hemalatha, K. L. (2023). AI interview agent for predicting communication skills and personality traits. International Journal of Engineering Research & Technology (IJERT), 11(8), RTCSIT–2023. https://doi.org/10.17577/IJERTCONV11IS08018

Rädel-Ablass, K., Schliz, K., Schlick, C., Meindl, B., Pahr-Hosbach, S., Schwendemann, H., … & Miersch, C. (2025). Teaching opportunities for anamnesis interviews through AI-based teaching role plays: A survey with online learning students from health study programs. BMC Medical Education, 25(1), 259. https://doi.org/10.1186/s12909-025-06756-0

Rai, A. N. (2025, March 17). AI mock interview chatbot using Gen AI. International Journal of Science, Engineering and Technology, 13(2), 189–197. https://www.ijset.in/wp-content/uploads/IJSET_V13_issue2_242.pdf

Rao, G. S., Jaiganesh, M., & Parida, P. K. (2025, April). AI-powered virtual job interview simulator using natural language processing. In 2025 8th International Conference on Trends in Electronics and Informatics (ICOEI) (pp. 1413–1421). IEEE. https://doi.org/10.1109/ICOEI65986.2025.11013504

Røed, R. K., Baugerud, G. A., Hassan, S. Z., Sabet, S. S., Salehi, P., Powell, M. B., … & Johnson, M. S. (2023). Enhancing questioning skills through child avatar chatbot training with feedback. Frontiers in Psychology, 14, 1198235. https://doi.org/10.3389/fpsyg.2023.1198235

S, P., Siranjeevi, K., Kumar, N. V., Pathmesh, G., & Ponnarasu, A. (2025, May). NexInterview—AI-driven mock interview preparation platform. International Journal of Advanced Research in Science, Communication and Technology, 5(7), 26835. https://www.ijarsct.co.in/Paper26835.pdf

Sahani, K. K., Khan, M. S., Khatwani, S., Gupta, S., & Dubey, A. (2025). A smart interview simulator using AI avatars and real-time feedback mechanisms (AI avatar for interview preparation). International Journal of Engineering Technologies and

ISSN: 2473-4901
v11 n6438

Management Research, 12(5), 66–75. https://doi.org/10.29121/ijetmr.v12.i5.2025.1618

Sahu, A., Khare, R. K., Singh, Y. R., & Sahu, Y. (2025, June). AI interviewer using generative AI. In International Conference on Advances and Applications in Artificial Intelligence (ICAAAI 2025) (pp. 1231–1240). Atlantis Press. https://doi.org/10.2991/978-94-6463-738-0_94

Senthilkumar, K., Ranjith, S., Sivasakthi, M., & Ramvignesh, R. (2025, March). AI-based mock interview system using natural language processing. In 2025 International Conference on Advanced Computing Technologies (ICoACT) (pp. 1–6). IEEE. https://doi.org/10.1109/ICoACT63339.2025.11005032

Siswanto, J., Suakanto, S., Andriani, M., Hardiyanti, M., & Kusumasari, T. F. (2022). Interview bot development with natural language processing and machine learning. International Journal of Technology, 13(2), 274–285. https://doi.org/10.14716/ijtech.v13i2.5018

Takeuchi, N., & Koda, T. (2021, September). Job interview training system using multimodal behavior analysis. In 2021 9th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW) (pp. 1–3). IEEE. https://doi.org/10.1109/ACIIW52867.2021.9666270

Golande, S. V., Dandage, P., Jadhav, A., Mohite, P., & Shahane, A. (2025). Mock interview evaluator powered by AI. Excel Journal: Technology, Engineering, & Management Research, 12(2), 1–9. https://www.researchgate.net/publication/391976964_MOCK_INTERVIEW_EVALUATOR_POWERED_BY_AI

Vardarlıer, P. (2023). A system that allows users to have a job interview experience. Sustainability, 15(22), 16031. https://doi.org/10.3390/su152216031

Wilkie, L., & Rosendale, J. (2024). Efficacy and benefits of virtual mock interviews: Analysing student perceptions of digital employment preparations. Journal of University Teaching and Learning Practice, 21(1), 177–195. https://doi.org/10.53761/rvtxt659

APPENDIX A
Tables

Papers	Gamification	Technology	Strengths	Limitations
(Ashrafi et al., 2024)	Immersive Metahuman avatars in VR/AR/desktop	Unreal Engine (Metahuman), Convai (Chatbot), Meta Quest 3, Empatica Embrace+ (biosensor), TTS/STT modules	Photorealism, emotional impact tracking, comparative analysis	No real-time feedback, lacks adaptive coaching, AR in progress
(Daryanto et al., 2025)	Adaptive LLM-based simulation with dialogic feedback	Web app with GPT-3.5/4 and transcript annotation	Realistic, interactive simulation, dialogical feedback	Lacks multimodal feedback, not domain-specific
(Vardarlıer et al, 2023)	Gamified scoring through points and achievements, immersive VR-based simulations	Web-based system, NLP, emotion and gesture analysis, VR headset, chatbot, sensors	Gamified scoring, immersive UX, NLP & emotion tracking	Feedback general, no validation study
(Leutner et al., 2023)	Cognitive ability assessment via games (Shapedance, Numerosity)	Machine learning (Ridge Regression with Bias Penalization), ICAR, CRT, HireVue platform	Valid and fair cognitive scoring, positive user feedback	Concerns over face validity, narrow task types
(Geng et al., 2024)	Immersive VR agents and biofeedback	VR headset with EEG/ECG-enabled virtual agents	Reduced anxiety, improved performance, multimodal	Requires biofeedback hardware, small sample

Table 1: Summary of Recent Advancements in Gamification-Based Job Interview Systems

Papers	Soft Skill Focus	Key AI Technologies Used	Strengths	Limitations
(Rao et al., 2025)	Technical, behavioral, situational questions; response relevance, semantic coherence, sentiment, keywords.	GPT/BERT, semantic similarity, sentiment analysis, and Google Speech-to-Text (STT) for speech-to-text.	Scalable, adaptive QG, heatmap feedback, role-based scoring	No emotion recognition, limited non-verbal feedback
(Senthilkumar et al., 2025)	Fluency, coherence, and knowledge are assessed through verbal communication and behavioral observation.	Speech-to-Text (Mozilla DeepSpeech), Text-to-Speech (Google TTS, Amazon Polly), Natural Language Processing (GPT, T5, BERT, RoBERTa), and Computer Vision (OpenCV, MediaPipe).	Multimodal feedback (verbal and behavioral), real-time evaluation	Limited scenario variation

Papers	Soft Skill Focus	Key AI Technologies Used	Strengths	Limitations
(Nofal et al., 2025)	Leadership, communication, and domain knowledge; quantitative reliability metrics; and bias analysis	Unity 3D + OpenXR for the VR environment, ChatGPT for question generation and feedback, Wit. AI for Text-to-Speech, Whisper. AI for Speech-to-Text, BART/topic modeling & Distil-BERT for semantic similarity, and RoBERTa for the scorer model.	Bias analysis, consistent scoring, VR immersion, real-time feedback	Hardware intensive, no gaze detection, lab-only testing
(Sahani et al., 2025)	Key qualities for effective communication and professional aptitude, emphasizing clear expression, topical relevance, and proficiency in both technical and interpersonal skills.	GPT-3, Whisper, Google STT/TTS, React.js	Immersive, scalable 3D avatar interface with real-time, multi-modal feedback. High STT/TTS accuracy, low latency (<2.5s)	No non-verbal analysis lacks multilingual support
(Bachhav et al., 2023)	Common hiring assessments include general job-skill Q&A, soft-skill simulations, and aptitude tests (covering logical and verbal reasoning).	STT, TTS, web-based layered architecture	Aptitude test, realistic Q&A, anxiety reduction	No validation study, no emotional feedback, no coding tasks
(Chou et al., 2022)	Intrinsic and DISC personality traits, along with facial emotions, head poses, speaking rate, amplitude, and pitch, contribute to interview performance.	Linear regression for scoring, Gamma distribution, and Automatic Relevance Determination (ARD).	Personality/behavioral modeling, asynchronous simulations	No live interaction, no adaptive feedback
(Namratha et al., 2024)	Factors assessed include content accuracy, response delivery, emotional state (via facial expressions), confidence levels (through voice analysis), and sentiment.	NLP, along with Transformer-based models for STT conversion, and Convolutional Neural Networks (CNNs) for image analysis	Emotion & voice analysis, adaptive feedback	Generic scoring models, unclear personalization logic
(Siswanto et al., 2022)	Evaluation of competency levels using the STAR model (Behavioral Event Interview) based on predefined categories.	NLP techniques, such as tokenization, stop-word removal, stemming, and part-of-speech tagging. Machine Learning methodologies, including Bayesian inference and TF-based weighting	Real-time competency evaluation, scalable	Behavior only via text, lacks audiovisual feedback

Papers	Soft Skill Focus	Key AI Technologies Used	Strengths	Limitations
(Hasan et al., 2023)	Language learning, mental health, public speaking, social skill development, and emotionally expressive communication	Large Language Models (LLMs), STT, TTS, emotion modeling, and avatars (within a 3D game engine).	Multilingual, emotion-aware avatar, personalized coaching	Short duration, no memory persistence, demo stage

Table 2: Summary of Interview Systems Focused on Soft Skills

Papers	Main Features	Technologies Used	Strengths	Limitations
(Sahu et al., 2025)	Generates coding questions from resumes; cheat detection; live editor	LLMs (GPT), facial/voice analysis, behavioral metrics	Context-aware question generation, cheat detection, interactive coding	Facial/voice model performance unclear, lacks soft skill evaluation
(Gomez et al., 2025)	Whiteboard-style technical interviews, code and voice analysis	Multimodal NLP, whiteboarding tools, and feedback systems	Realistic simulation, high user engagement, multimodal analysis	No emotion detection, lacks plagiarism control
(Qin et al., 2024)	Generates skill-aligned technical questions using deep learning and graph-based recommendation	Skill entity mining, question generation, neural ranking models	High relevance of Questions, user skill adaptability, modular design	Limited soft skill integration, rule-based rigidity in places
(Dougherty et al., 2025)	Coding interview benchmark with formal verification	Formal methods, Lean 4, coding benchmark creation	Verified test cases, benchmarking standard for interviews	No user interaction features, lacks AI/NLP analysis
(Dascalescu et al., 2025)	Generates edge case test cases for coding contests	LLMs, test case generation, code evaluation	Complement human test design, increases grading accuracy	Not a traditional interview system, no behavioral component
(Chou et al., 2022)	Mock interview platform for tech and behavioral evaluation	AI evaluation models (unspecified), behavioral scoring	Dual focus on technical and behavioral, asynchronous simulation	No live feedback, lacks scenario customization

Table 3: Summary of Recent Advancements in Technical Job Interview Systems