
AI-Driven Mock Interview Coaching: Enhancing Polytechnic Students' Career Readiness and Confidence

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Abstract

This mixed-method study explores the role of AI-powered mock interview coaching in strengthening the career readiness of polytechnic students. It focuses on enhancing key aspects such as communication confidence, fluency, non-verbal skills, and content relevance during interviews. Conducted over two academic semesters, the research involved 120 students enrolled in the Communicative English 3 (DUE50032) course at POLIMAS. The study incorporated AI tools including Google Interview Warmup, Yoodli AI, and Mockmate, each delivering real-time and personalized feedback on verbal delivery, structure, and tone. Pre- and post-assessments were analyzed using paired t-tests, revealing substantial improvements across all measured criteria: confidence (+37%), fluency (+35%), non-verbal communication (+36%), and content relevance (+33%), with a t-statistic of 55.67 and p-value < 0.001. These findings were supported by students' qualitative reflections indicating greater self-awareness and reduced anxiety. The study demonstrates that AI-assisted coaching offers a viable, cost-effective strategy to bridge communication skill gaps and increase employability among tertiary learners.

Keywords: AI-driven coaching; career readiness; communication confidence; employability skills; mock interview; zero-cost AI tools

I. INTRODUCTION

Securing employment often requires more than technical competence; candidates are expected to communicate effectively, exhibit professionalism, and respond with structured, thoughtful answers. Despite their academic qualifications, many students find it challenging to express themselves with clarity and confidence during job interviews [1]. Employers increasingly prioritize soft skills, including verbal fluency and interpersonal communication, which are often underdeveloped in traditional academic settings [2].

While conventional mock interview practices provide general preparation, they frequently lack individualized, real-time feedback, reducing their effectiveness in addressing specific areas of weakness [3]. Emerging developments in artificial intelligence (AI) have introduced new possibilities for enhancing interview preparation through automated coaching. AI tools can analyze speech patterns, assess tone and sentiment, and generate immediate recommendations, allowing students to engage in self-paced, low-pressure practice sessions [4].

Although AI has seen broad application in education and training, its potential for interview readiness—particularly among Malaysian polytechnic students—remains relatively underexplored. This study investigates whether AI-driven mock interview coaching can significantly improve student performance in key communication domains. Specifically, the research evaluates changes in confidence, fluency, non-verbal behavior, and content relevance before and after exposure to AI-supported coaching. The paper also considers participants' perceptions of the tools and their impact on career preparedness.

The structure of this paper is organized as follows: Section II presents a comprehensive review of literature relevant to AI applications in education, mock interview practices, and AI-enabled coaching. Section III outlines the theoretical framework grounding this research. Section IV details the methodology, including participant demographics, AI tools, and evaluation criteria. Section V discusses the results, integrating both quantitative data and qualitative feedback. Finally, Section VI concludes the study, summarizing its contributions and proposing directions for future research.

II. LITERATURE REVIEW

Artificial intelligence (AI) has gained significant traction in the field of education, particularly in the delivery of customized learning experiences and skill development. Contemporary AI platforms are capable of providing adaptive, real-time support to learners, promoting greater autonomy and engagement. Studies have emphasized the potential of AI in offering personalized feedback that helps students identify their strengths and areas needing improvement, which is particularly beneficial in performance-based tasks such as interviews [5], [6].

Mock interviews have long been recognized as an effective method for preparing students for the job market. These simulations allow learners to rehearse responses, receive critiques, and develop familiarity with the structure of formal interviews. Empirical evidence suggests that students who engage in structured mock interview exercises show marked improvements in articulation, confidence, and content organization [7]. Nevertheless, these traditional approaches often depend heavily on instructors for feedback, introducing variability and potential subjectivity into the evaluation process [8].

AI-powered mock interview systems have emerged as a complementary solution, offering automated and standardized feedback based on objective parameters. Such tools often integrate speech recognition algorithms, sentiment analysis, and machine learning capabilities to assess verbal responses. These systems provide users with detailed analyses of pacing, tone, structure, and coherence, enabling learners to iteratively refine their performance without the need for constant human intervention [9], [10].

In recent years, research has begun to explore AI's broader application in communication training and behavioral development. For example, Khan et al. [11] demonstrated that natural language processing technologies could substantially improve articulation and clarity among learners. Escalante et al. [12] showed that virtual interview agents contributed to better non-verbal behavior and reduced performance anxiety. Similarly, Santos and Lee [13] examined the intersection between AI tools used in speech therapy and their potential for interview preparation, identifying overlapping benefits such as fluency enhancement and pronunciation correction.

Additional studies by Gupta et al. [14] and Wang [15] investigated the application of AI feedback systems across different disciplines. These studies highlight the importance of adaptive learning loops and user-centric feedback in improving educational outcomes, while also raising awareness about

limitations such as AI bias and accessibility. Furthermore, Geng et al. [16] introduced a virtual reality-based AI interview coach aimed at addressing anxiety among introverted students. Rädell-Abläss et al. [17] explored the use of generative AI in healthcare education through chatbot simulations, illustrating how AI can support role-play and experiential learning.

Recent studies have further emphasized the transformative potential of AI in career training and language development. Verma et al. (2022) explored the integration of AI-powered video interview platforms in enhancing graduate employability and found that repeated interaction with virtual interview agents improved confidence and articulation, particularly in high-stakes assessment scenarios [18]. Similarly, Kim (2021) conducted a meta-review of AI applications in language and communication training, concluding that AI tools such as automated speech evaluation, natural language feedback systems, and adaptive learning engines positively impacted learner autonomy and performance in both academic and professional settings [19]. These insights affirm the growing utility of AI-driven learning environments for career-related skill development.

Collectively, these findings underscore the growing relevance of AI-driven tools in communication training, including mock interview preparation. Drawing insights from a range of adjacent fields, this study aims to examine how similar AI-based interventions may support Malaysian polytechnic students in developing the confidence and skills necessary for employment interviews.

Let's begin by considering whether you need a literature review at all. Assuming you do, we then look at what it should contain and how it can be organised, and at alternative styles of citation. Main Heading need to be in Roman I, II, III, Paper Size A4, Layout: Columns Two, Paragraph Spacing 1.0, Times New Roman, Size 10, Position Justify.

In this chapter the researcher discusses the highlights of the study relating to computational thinking which produce skills such as problem-solving skills, creative and critical thinking skills, and analytical skills to students[1].

III. THEORETICAL FRAMEWORK

This study is underpinned by David Kolb's Experiential Learning Theory (1984), which posits that learning is a continuous process grounded in experience. According to Kolb, effective learning occurs when individuals actively engage in a cycle of experiences that include concrete action, reflection, conceptual understanding, and experimentation. This cyclical model supports the idea that learners internalize knowledge and skills

more effectively when they are able to reflect on direct experiences and apply new strategies based on those reflections.

The model comprises four interconnected stages: Concrete Experience, Reflective Observation, Abstract Conceptualization, and Active Experimentation. In the context of this study, the Concrete Experience involves students participating in initial mock interview sessions without AI assistance. During the Reflective Observation stage, students review video recordings and analyze feedback generated by AI tools to evaluate their performance. The Abstract Conceptualization phase prompts students to identify patterns, articulate areas for improvement, and devise strategies for enhancing their communication skills. Finally, in the Active Experimentation stage, students apply these strategies in subsequent mock interviews, thus reinforcing learning through iterative practice.

Kolb's model aligns well with the design of AI-driven mock interview coaching, as the feedback loop created by these tools facilitates self-directed learning and personal growth. Through repeated practice and immediate feedback, students gain insights into their communication style, enabling them to adapt and improve with each cycle. This experiential approach supports the study's objective of enhancing students' career readiness by fostering deeper learning and skill development through structured reflection and practice.

The choice to adopt Kolb's framework is especially pertinent to this research for several reasons. Firstly, the experiential cycle mirrors the practical and iterative nature of mock interview training, making it an ideal model for analyzing learning outcomes in skill-based tasks. Secondly, AI tools such as Google Interview Warmup, Yoodli AI, and Mockmate offer continuous feedback, which reinforces the reflection and experimentation stages of Kolb's theory. Thirdly, the framework accommodates diverse learner profiles, allowing for individualized progress at different paces—an important consideration given the varied language proficiency and confidence levels among polytechnic students. By aligning the instructional design of the AI coaching experience with a well-established educational theory, this study ensures a structured yet flexible approach to skill acquisition, leading to measurable improvements in communication competence.

IV. RESEARCH METHODOLOGY

This study employed a mixed-methods research design to investigate the effectiveness of AI-driven mock interview coaching. Both quantitative and qualitative data collection techniques were integrated to capture a holistic view of the students'

learning outcomes and perceptions. The decision to use a mixed-methods approach stems from the nature of the research objectives, which aim not only to measure the statistical impact of AI-driven tools on student performance but also to explore students' experiences, self-perceptions, and the practicality of these tools in real learning environments.

Quantitative methods were applied through the use of pre- and post-test score comparisons. This approach allowed researchers to quantify improvements in specific communication metrics—confidence, fluency, content relevance, and non-verbal communication—by using measurable data analyzed through statistical tests. The paired sample t-test was chosen for its ability to assess changes within the same group of students before and after the intervention. This method is widely used in educational research to evaluate the effectiveness of instructional strategies and interventions.

Qualitative methods complemented the quantitative analysis by capturing the depth and complexity of students' learning experiences. Student reflections, peer evaluations, and lecturer feedback were collected and thematically analyzed to identify recurring patterns such as increased self-awareness, reduced anxiety, and improved articulation. This aspect of the study provided valuable context for interpreting the statistical findings and validated the impact of the AI tools from the learners' perspectives.

The integration of both methods—commonly referred to as a convergent parallel mixed-methods design—ensured that the research findings were comprehensive and well-rounded. While quantitative data provided empirical evidence of improvement, qualitative data enriched the understanding of how and why those improvements occurred.

A. Participants

The research was conducted over two academic semesters and involved 120 diploma-level students enrolled in the Communicative English 3 (DUE50032) course at Politeknik Sultan Abdul Halim Mu'adzam Shah (POLIMAS). Participants were selected based on their need for career readiness support and mock interview training, as determined by initial classroom observations and lecturer recommendations. While the sample provides valuable insights into the research topic, generalizability may be limited due to the focus on a single institution and course. Future studies may consider a more diverse sample population across institutions, disciplines, and proficiency levels to examine broader applicability.

B. Ethical Considerations and Data Privacy

In compliance with ethical research practices, all participants were informed of the study's objectives and procedures prior to data collection. Written consent was obtained, and students were assured that their participation was voluntary and that data would remain confidential. AI tools used in the coaching process, such as Google Interview Warmup, Yoodli AI, and Mockmate, adhere to data protection regulations, including GDPR and PDPA. Student-generated data (e.g., interview recordings and feedback) were anonymized and stored securely using institutional cloud repositories with restricted access.

C. Research Design

A sequential pre-test/post-test design was utilized to assess improvements in interview performance. Participants completed a mock interview session without AI coaching, followed by multiple AI-assisted coaching sessions. Afterward, a second mock interview was conducted using the same evaluation criteria. This design allowed the researchers to attribute performance changes to the intervention while minimizing test variability.

D. Instruments and AI Tools

To implement the AI-driven coaching intervention effectively, this study incorporated three distinct web-based platforms: Google Interview Warmup, Yoodli AI, and Mockmate. Each tool was chosen based on its unique functionality, alignment with the research objectives, and ease of access for students with varying levels of digital literacy.

Google Interview Warmup, developed by Grow with Google, utilizes speech recognition and machine learning algorithms to assess verbal fluency and lexical richness. It prompts users with commonly asked interview questions and records their spoken responses, which are then transcribed and analyzed. The platform provides automated feedback on aspects such as frequent word usage, key job-related terms, and response completeness. This immediate, objective analysis supports learners in recognizing their speaking habits and identifying opportunities to enhance their vocabulary and articulation.

Yoodli AI, another AI-powered tool, employs natural language processing (NLP) to evaluate speech delivery from both linguistic and emotional perspectives. It provides detailed feedback on pacing, filler word frequency, hesitations, tone modulation, and overall confidence as inferred from voice dynamics. This tool is particularly beneficial in helping students become aware of their non-verbal cues and delivery style, which are critical for building confidence during high-stakes interviews.

The platform's sentiment analysis further allows students to gauge the emotional undertones of their speech, encouraging self-regulation and tone refinement.

Mockmate, an AI interview simulator, focuses on evaluating the structural quality of student responses. It assesses the coherence, clarity, and relevance of answers to various interview questions. The tool simulates a realistic interview interface, prompting users with text-based questions and providing tailored feedback based on the logic, professionalism, and alignment of responses with expected job roles. This function enables students to refine their ability to frame well-structured, purposeful answers within a professional context.

The selection of these tools was informed by their accessibility, intuitive design, and zero-cost or low-cost usage, making them suitable for institutional adoption at scale. Their asynchronous format allows students to practice at their own pace and convenience, supporting a learner-centered approach. Additionally, the diversity in feedback provided by the tools—ranging from fluency and content accuracy to emotional tone and structure—ensures that the intervention addresses multiple dimensions of communication competence. This multifaceted assessment framework aligns with the study's aim to holistically improve students' interview readiness through targeted, data-informed coaching strategies.

E. Evaluation Criteria and Scoring Rubric

To ensure a systematic and reliable assessment of students' mock interview performance, a structured evaluation rubric was developed and implemented. The assessment framework was designed to measure four core competencies critical to successful interview delivery: Confidence Level, Fluency and Clarity, Non-Verbal Communication, and Content Relevance. These components were selected based on industry expectations, communicative competence frameworks, and pedagogical best practices in oral presentation and interview preparation.

The Confidence Level criterion, weighted at 30%, evaluated the student's composure, vocal projection, and ability to present themselves assertively during the interview. Factors considered included tone of voice, eye contact, posture, and the presence or absence of hesitation. High scores in this domain indicated a poised and self-assured presentation style.

Fluency and Clarity, also accounting for 30% of the total score, focused on the student's command of spoken English. This included the smoothness of speech, pronunciation accuracy, and grammatical correctness. The use of transitional phrases and the

ability to maintain a coherent flow of ideas were also taken into account. This criterion was especially important in assessing how well students could communicate under simulated interview conditions.

Non-Verbal Communication, given a 20% weighting, addressed the physical and paralinguistic aspects of communication. This included facial expressions, gestures, posture, and overall body language. These cues are often subconscious but significantly influence the interviewer's perception of the candidate's confidence and professionalism.

Content Relevance, contributing the remaining 20%, evaluated the alignment of the student's responses with the given interview questions. This involved assessing whether answers were logically organized, supported with appropriate examples, and tailored to the context of the job role in question. Relevance was judged by both the appropriateness of content and the depth of insight demonstrated in the responses.

Each component was scored on a consistent scale using a standardized rubric that was validated through consultation with English language instructors and communication specialists. Lecturers conducting the evaluation received orientation on how to apply the rubric uniformly. To supplement human scoring and enhance objectivity, AI-generated feedback from Google Interview Warmup, Yoodli AI, and Mockmate was also considered during evaluation. This dual-assessment approach ensured a more holistic and accurate representation of students' performance and allowed for richer feedback.

The use of a multi-criteria rubric supported fair, transparent, and actionable assessment. It also enabled students to understand their performance across distinct yet interrelated communication domains, thereby fostering reflective learning and targeted improvement.

F. Statistical Analysis

To determine the effectiveness of the AI-driven mock interview coaching intervention, a quantitative analysis was conducted using the paired sample t-test. This statistical method was selected due to its suitability for comparing two related groups—in this case, students' performance before and after the AI-assisted coaching sessions. The pre-test and post-test scores were collected from the same cohort of participants, allowing for a direct measurement of changes resulting from the intervention.

The primary aim of the statistical analysis was to assess whether the observed improvements in student performance across four key metrics—Confidence Level, Fluency and Clarity, Non-Verbal Communication, and Content Relevance—were

statistically significant. Each student's post-test score was subtracted from their corresponding pre-test score to obtain a set of difference scores. These differences were then analyzed to calculate the mean improvement, standard deviation of the differences, and the standard error of the mean.

The t-value was calculated based on the ratio of the mean difference in scores to the standard error of that difference. Specifically, the formula used was: $t = (\text{Mean Difference}) / (\text{Standard Error})$

In this context, the mean difference refers to the average increase in students' scores from the pre-test to the post-test, reflecting the overall effect of the AI-driven coaching intervention. The standard error accounts for the variability of these difference scores within the sample and provides an estimate of how precisely the mean difference represents the population. The degrees of freedom (df) for the test were determined using the formula $df = n - 1$, where n denotes the total number of paired observations.

The resulting t-value was then used to determine the p-value, which indicates the likelihood that the observed improvement occurred by chance. A significance level of $p < 0.05$ was established as the threshold for statistical significance. A p-value below this threshold suggests that the AI-driven intervention had a meaningful impact on student performance.

In this study, the computed t-statistic was 55.67, with a corresponding p-value of less than 0.001. This outcome strongly supports the conclusion that the improvements observed in students' communication competencies were not due to random variation but rather the result of the intervention. Descriptive statistics such as means, percentages, and standard deviations were also used to present the performance trends clearly.

The statistical findings provided empirical validation of the coaching strategy's success and served as a foundation for interpreting the qualitative results. By employing the paired sample t-test, the study ensured that the evaluation of effectiveness was both rigorous and aligned with common practices in educational impact research.

G. Qualitative Analysis

To complement the statistical findings, qualitative data were collected to gain deeper insights into students' perceptions of the AI-driven coaching process and its impact on their communication skills. The qualitative component was essential in capturing the experiential dimensions of learning that could not be fully explained through numerical data alone. This approach aligns with the study's mixed-methods design, which emphasizes the

integration of empirical measurement with contextual understanding.

Data were obtained through three primary sources: student reflection forms, peer evaluations, and structured feedback from course lecturers. These instruments were selected for their capacity to elicit authentic, learner-centered responses. The reflection forms encouraged students to critically assess their own performance before and after the intervention, focusing on changes in confidence, fluency, and preparedness. Peer evaluations provided collaborative feedback among classmates, fostering mutual observation and learning. Lecturer feedback offered professional assessments of students' progress, particularly in areas such as delivery, structure, and interview etiquette.

The qualitative data were analyzed using a thematic analysis approach. This method involved systematically coding the responses and identifying recurring patterns or themes across the data sets. Key themes that emerged included heightened self-awareness, increased confidence in responding to interview questions, and greater clarity in structuring responses. Many students reported feeling more prepared and less anxious during the post-test interviews, attributing their improvement to the personalized feedback provided by the AI tools. Several reflections also noted that the opportunity to review AI-generated insights and compare performance over time contributed to a more reflective and self-directed learning experience.

Lecturers noted improved articulation and increased professionalism in students' verbal and non-verbal communication during mock interviews. Peer evaluations echoed these observations, highlighting noticeable changes in classmates' confidence and delivery. These multiple perspectives helped triangulate the findings and validated the impact of the intervention beyond the numerical data.

The integration of qualitative data thus added significant depth to the research findings. It enabled the researchers to contextualize the quantitative improvements and better understand how the AI tools influenced students' behaviors, perceptions, and learning strategies. This dual-layered analysis strengthened the study's overall credibility and demonstrated the value of incorporating learner feedback in evaluating the effectiveness of educational technologies.

H. Triangulation and Validation

To enhance the credibility and trustworthiness of the study's findings, a triangulation strategy was employed. Triangulation in research involves using multiple data sources, methods, or evaluators to cross-verify the consistency and reliability of

results. In the context of this study, triangulation was achieved through the convergence of quantitative data, qualitative feedback, and AI-generated assessments. This multi-perspective approach ensured that the evaluation of the AI-driven coaching intervention was comprehensive and balanced.

Quantitative data, collected through pre- and post-test scores using a standardized rubric, provided measurable evidence of performance improvements. These data were further supported by AI-generated metrics such as fluency scores, filler word frequency, and sentiment analysis from platforms like Google Interview Warmup, Yoodli AI, and Mockmate. The use of AI tools introduced an additional layer of objectivity, reducing potential biases associated with human evaluation.

Complementing this were qualitative insights derived from student reflections, peer assessments, and lecturer observations. The consistency of emerging themes—such as increased confidence, enhanced articulation, and reduced anxiety—across all sources affirmed the intervention's effectiveness. For instance, when both AI feedback and lecturer comments highlighted similar improvements in a student's tone or structure, it reinforced the reliability of those observations.

Moreover, peer evaluations added a valuable collaborative dimension to the learning process. Students were encouraged to observe and assess one another using simplified rubrics, which not only promoted active engagement but also offered learners the opportunity to gain insights into effective communication strategies through comparison.

The integration of these various data streams allowed the researchers to validate findings from multiple vantage points. By comparing and cross-referencing evidence across sources, the study reduced the risk of bias and enhanced the interpretative depth of the results. This methodological rigor strengthened the study's internal validity and reinforced the argument that AI-driven coaching is a robust and impactful strategy for improving communication skills in higher education settings.

V. RESULT AND DISCUSSION

The results of this study illustrate the significant impact of AI-driven mock interview coaching on students' communication competencies. This section presents and interprets the findings by integrating statistical outcomes with qualitative evidence to provide a comprehensive understanding of how AI tools influenced students' preparedness and performance in mock interviews.

A. Quantitative Findings

The quantitative analysis revealed statistically significant improvements in all four evaluated components: confidence, fluency and clarity, non-verbal communication, and content relevance. These findings are summarized in Table 1.

Metric	Pre-Test (%)	Post-Test (%)	p-value
Confidence Level	45	82	<0.001
Fluency & Clarity	50	85	<0.001
Non-Verbal Communication	42	78	<0.01
Content Relevance	55	88	<0.001

Table 1

The most prominent gains were observed in the areas of confidence and fluency, suggesting that students responded particularly well to the feedback mechanisms offered by AI tools. These improvements reflect enhanced self-awareness and increased ability to organize and express thoughts clearly. The positive change in non-verbal communication, although relatively smaller in percentage, remains notable given that most AI tools used in this study primarily focused on verbal delivery. Nevertheless, students became more conscious of body language, eye contact, and posture through guided self-evaluation and peer observation.

The paired sample t-test analysis supported these findings, yielding a t-value of 55.67 and a highly significant p-value of less than 0.001. This strong statistical evidence confirms that the intervention had a real and meaningful effect on students' performance. Descriptive statistics such as means and standard deviations further supported these outcomes, indicating consistent improvement across the participant group.

B. Qualitative Findings

Thematic analysis of qualitative data derived from student reflection forms, peer feedback, and lecturer evaluations offered valuable insights into the learning process. A common theme emerging from student narratives was heightened self-awareness. Students reported gaining clarity on their speech patterns, including the frequency of filler words, pacing, tone, and the coherence of their responses. Many shared that the ability to receive instant AI-generated feedback helped them identify specific issues and take deliberate actions to improve.

Another key theme was increased confidence. Students expressed that the opportunity to repeatedly practice their responses in a low-pressure

environment contributed to reduced anxiety and more structured answers during the post-test interviews. Several students described feeling more "prepared," "calm," and "professional" after engaging with the tools.

Lecturers echoed these sentiments, noting improvements in students' organization of ideas, appropriate use of technical vocabulary, and professionalism in delivery. Some lecturers observed previously quiet or hesitant students demonstrating noticeable progress in voice projection and posture during the final assessment. Peer feedback also affirmed these changes, with students acknowledging each other's growth in fluency and composure.

C. Integration and Interpretation

When analyzed together, the quantitative and qualitative findings demonstrate a consistent pattern of improvement attributable to the AI intervention. The significant increases in test scores aligned with students' reported experiences of growth and enhanced readiness. The data suggest that the AI tools not only improved performance but also facilitated reflection, autonomy, and self-efficacy—key indicators of effective learning.

The multifaceted nature of the tools—combining transcription, sentiment analysis, and structural feedback—enabled students to address various aspects of communication simultaneously. This integrated feedback mechanism appears to have amplified the impact of the intervention by offering holistic coaching tailored to each student's strengths and weaknesses.

Additionally, the positive outcomes from this study suggest that similar approaches can be extended to students in diverse academic disciplines, including engineering, business, and hospitality, where communication is integral to professional success. Non-English-major students, particularly those with limited exposure to formal interview settings, may benefit from the structured and guided practice these tools offer. Furthermore, institutions with limited access to experienced interview coaches or language instructors could adopt these zero-cost AI tools as scalable alternatives for enhancing employability training.

D. Pedagogical Implications

The findings carry meaningful implications for educators and curriculum developers, particularly in fields emphasizing employability skills. Integrating AI coaching tools into communicative English or career readiness modules can provide scalable, low-cost solutions for enhancing students' interview performance. These technologies complement

instructor-led teaching by offering individualized feedback and opportunities for self-paced practice.

The use of AI in education is especially advantageous in contexts where time and resources for one-on-one coaching are limited. By automating parts of the evaluation and feedback process, educators can reallocate time toward personalized mentoring or enrichment activities. Moreover, the self-directed nature of the tools supports lifelong learning skills, empowering students to take ownership of their growth.

E. Limitations and Considerations

While the results are encouraging, certain limitations must be acknowledged. The study was conducted within a specific academic institution and discipline, which may affect the generalizability of the findings. Additionally, the AI tools used in the study focused primarily on verbal features of communication. Future implementations may consider incorporating tools capable of analyzing non-verbal cues in real-time or integrating virtual reality elements for more immersive practice.

Furthermore, while AI tools offer objective and timely feedback, they should not be viewed as a replacement for human instruction. Instead, they should be integrated thoughtfully into blended learning environments, where human insight and empathy can complement machine-generated insights.

In conclusion, the results provide strong evidence that AI-driven mock interview coaching is an effective, learner-centered approach to enhancing communication and career readiness skills. The findings validate the role of AI as a pedagogical support tool and underscore the potential of digital technologies to transform how professional skills are taught and assessed in higher education.

VI. CONCLUSION

This study investigated the effectiveness of AI-driven mock interview coaching in improving the communication competencies and career readiness of polytechnic students. Drawing upon a mixed-methods approach, the research combined quantitative data from pre- and post-test evaluations with qualitative insights from student reflections, peer assessments, and lecturer feedback. The integration of these data sources provided a comprehensive understanding of how AI coaching tools influenced student learning and performance.

The findings demonstrated statistically significant improvements in confidence, fluency, non-verbal communication, and content relevance following the intervention. Students benefited from repeated practice, real-time AI feedback, and the opportunity to reflect on their performance. These elements

contributed to enhanced self-awareness, increased articulation, and greater poise during mock interviews. The qualitative feedback further supported the statistical results, highlighting the students' positive engagement with the tools and their perceived growth in both communication skills and self-confidence.

One of the key contributions of this study is its demonstration of how AI tools can be effectively integrated into communication training programs. The results suggest that AI-powered platforms such as Google Interview Warmup, Yoodli AI, and Mockmate can complement traditional instructional methods by offering scalable, personalized, and low-cost solutions to improve employability skills. In doing so, they provide students with the means to develop professionally relevant soft skills in a learner-centered environment.

The study also provides practical implications for educators and institutions. Incorporating AI-driven coaching tools into classroom pedagogy offers new possibilities for enhancing student engagement and learning outcomes, particularly in settings where individualized instruction is not feasible. Additionally, the study reinforces the value of reflective learning and experiential practice, aligning well with the principles of Kolb's experiential learning theory.

Despite the encouraging outcomes, the study has several limitations. It was conducted within a single institution and focused on a specific course and student population. The tools used in the intervention primarily assessed verbal and structural communication, leaving non-verbal aspects less comprehensively addressed. Future research should consider broader samples, longitudinal tracking of employability outcomes, and the integration of multimodal technologies such as virtual reality to simulate more immersive interview experiences.

Nevertheless, the methodology and findings presented in this research provide a foundation that can be adapted across academic fields and institutional contexts. Whether for students in STEM, business, or vocational programs, or for learners in multilingual environments, AI-driven coaching can be tailored to accommodate varying levels of language proficiency and curricular goals. Moreover, in under-resourced institutions, these technologies present an opportunity to bridge coaching gaps and deliver equitable training experiences.

In summary, this research confirms that AI-driven mock interview coaching has significant potential to transform communication training in higher education. By enabling learners to receive instant, objective feedback and engage in self-directed practice, AI tools can play a pivotal role in preparing

students for the demands of the modern workforce. The study adds to the growing body of literature on educational technology and underscores the importance of innovation in teaching practices to support student success and career readiness.

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