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AI-Driven Mock Interviews: A Catalyst for Enhanced Interview Performance

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Abstract - Mock interviews have long been recognized as a valuable tool for job seekers to enhance their readiness for real job interviews, providing invaluable insights into a candidate's communication, confidence, preparation, and time management skills. However, traditional human-to-human mock interviews can be expensive, offer limited attempts, may not always provide immediate feedback, and could potentially be influenced by personal biases. Additionally, they may not always provide the diverse range of interview scenarios that a candidate might encounter in the real world. In order to study the impact of AI-Powered mock interviews, this research utilizes Skill2030.com a platform that offers job seekers a realistic AI-powered mock interview experience with personalized feedback while promoting diversity and inclusivity. An ethical approach is followed by the researchers in utilizing AI by excluding protected parameters like age, gender, ethnicity, etc., from the analysis. The study involves 6619 interviews conducted for candidates from 998 colleges across India representing all tiers (Deemed Universities, IITs, Affiliated, and Autonomous Engineering Colleges) with a 30-70 rural/urban split. With a high positive feedback rate of 98.5%, the AI-based platform successfully provides realistic simulations, personalized feedback, and greater accessibility, enhancing overall job seekers' preparedness and success rates in India's competitive job market. Results gleaned from the feedback demonstrate that candidates with robust communication and writing skills exhibited a higher degree of confidence. A separate study of 500 candidates who used the AI-based platform as a learning tool to enhance their interview performance reveals promising and interesting patterns in how candidates improve by over 30% with consistent practice in parameters like technical correctness, pronunciation, intonation, fluency, and grammar.

Keywords— Digital Mock Interviews, AI based assessments, Automated communication skill training, job seekers' preparedness.

1. Introduction

Recognizing the pivotal role of English as a global language, the Indian Education System places significant emphasis on honing students' productive (speaking and writing) and passive (listening and reading) skills. However, despite the integration of English instruction into the mainstream curriculum, a

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considerable segment of the approximately 40 million students enrolled in higher education struggle to attain proficiency. This challenge is compounded by various factors, including a scarcity of proficient language educators, limited access to education in rural locales, ensuring uniform instructional standards, and addressing societal biases that impede effective communication. Particularly among rural students and marginalized demographics, these biases can hinder confidence, pronunciation, and vocabulary usage, often influenced by native language speech patterns (Repetajan, 2020).

In response to these multifaceted challenges, there is a pressing need for technological interventions. Ideally, such solutions should offer scalability, consistency, and address social biases, encompassing various language facets from speaking and writing proficiency to comprehension, domain knowledge, pronunciation, intonation, fluency, speed, and grammatical accuracy, both in spoken and written forms.

This paper delves into the ramifications of incorporating artificial intelligence into mock interview training, in order to address the prevalent demands in job interview preparedness. Leaning on the data derived from a comprehensive national survey, the study elucidates the potential structure and modus operandi of AI-empowered training tools, highlighting crucial metrics for spoken language evaluation. Offering a demographic snapshot of participants and an analysis of their performance metrics, this research critically evaluates the capability of real-time, AI-aided assessments to enhance learners' communication skills. The platform Skill2030.com is used in this study as an exemplar of such AI-powered platforms.

2. Literature Survey

The impact of language accents on perceptions associated with intelligence, kindness, solidarity, socioeconomic status, national origin, and ethnicity is well-documented (Lippi-Green, 1994; Nesdale & Rooney, 1990). In addition, accents may also influence selection decisions during interviews (SegrestPurkiss et al., 2006)

Familiarity and proficiency in the English language are often seen as vital to daily survival and societal integration, facilitating successful communication and fostering effective social and workplace relationships. For professionals in white-collar jobs, over a quarter of their time at work encompasses communication-focused tasks such as writing, reading, listening, and speaking. However, the journey towards English proficiency comes with various challenges for students, including vocabulary limitations, grammatical inaccuracies, imperfect pronunciation, poor active listening, fear of public speaking, self-expression difficulties, low confidence, and poor group communication abilities. Students from non-English speaking backgrounds particularly need guidance and encouragement to overcome these challenges (Patel, 2016).

Empirical research points towards a strong, positive relationship between English fluency and employability (Gaikwad, 2016; Gaikwad, 2019). Effective communication enhances working relationships and encourages healthy competitive environments (Gaikwad, 2016b). Mastery in English language communication skills can significantly elevate career prospects, assisting in job advancement and job security. Recent findings corroborate this, with a Harvard Business Review (HBR) report indicating that English proficiency is considered a fundamental job skill by over half of companies across numerous industries (Harvard Business Reviews [HBR], 2016).

Bharathi et al. surveyed a sample population comprising 618 undergraduate students and 18 English language teachers, establishing considerable concerns from both parties about the curriculum's deficiency in developing language competencies. Of the instructors engaged in the survey, 67% believed the syllabus fell short in cultivating listening skills, and 72% found its emphasis on spoken skills lacking. Moreover, over 60% of teachers felt the syllabus failed to focus adequately on presentation and written skills, identifying communication skills and vocabulary deficiency as significant challenges among students. From the perspective of students, the survey revealed difficulties in English communication (47%), comprehension skills and vocabulary (49%), and grammar (69%). Alarmingly, a vast majority (86%) of the students advocated for the necessity of practical learning methodologies over purely theoretical approaches for language teaching (Bharathi, 2016).

The National Employability Report (2019) stresses the essentiality of mastering programming and English language skills (presented in both written and spoken forms) to stay competitive in the job market. From a sample size of 60,000, the report found only 16% fit for sales roles and a meagre 2% ready for corporate communication (National Employability Report, 2019).

A. Impact of social interaction bias on language learning

Research on language learning bias in social interactions suggests that automated feedback mechanisms harbour several advantages for both students and faculties, significantly improving feedback quality in comparison to manual methods. A study involving 350 learners revealed that learners saved 30% of their time using a semi-automated feedback approach (Barker, 2011). Another survey about an online automated evaluation and feedback system's efficacy recorded positive experiences (Varank et al., 2014). The system was well-received for its conducive nature to learning performance, user satisfaction, simplicity, and assignment time savings.

B. Speech delivery issues faced by non-native English-speaking student

Social interactions play a crucial role in language learning (Kuhl, 2007; Laghari, 2014; Verga & Kotz, 2013; Borges & Salomão, 2003; Noriaki et al., 2017). Studies by Kuhl et al. (2007) and Verga & Kotz (2013) maintain this interaction's role in the earliest stages of language learning. Furthermore, opportunities for interaction with native English speakers are associated with improved English language learning (Noriaki et al., 2017). However, non-native English speakers often experience difficulties in speech delivery arising from pronunciation variations and accent differences. They are perceived to lack credibility due to accent-related processing difficulties and longer word durations, suggesting a stronger foreign accent (Baker et al., 2011; Radfar & Lengkanawati, 2020; Lev-Ari et al., 2017). Despite these challenges, it is highly recommended for non-native English-speaking students to participate in social interactions with native speakers to refine their speech delivery and pronunciation skills (Lev-Ari et al., 2017; Smiljanic et al., 2021; Luk, 1998; Klaassen&Bos,2010; Wong et al., 2006).

C. Language assessment tools and APIs for spoken language evaluation

Language assessment tools and APIs for spoken language evaluation: Toolkits for spoken language evaluation and APIs based on natural language processing (NLP) techniques have seen development to evaluate and improve spoken language (Hirschberg & Manning, 2015). These applications developed through NLP enable progress in machine translation, speech recognition, and speech synthesis. For example, (Wang et al. 2018) have developed an automatic system to assess natural spoken language proficiency, useful for interacting with electronic learning tools and candidates for formal qualifications. (Qian et al. 2017) investigated various neural network architectures to enhance the automated assessment of non-native children's speech. Additionally, a CD-ROM titled 'Voice Assessment: Speech-Language Pathology and Audiology & Medicine' was created as an educational tool for individuals interested in the production of spoken or sung human voice. This tool can be used to evaluate the effectiveness of teaching and learning materials related to education or health, within the context of technology-mediated education (Matta Vieira et al., 2009). Furthermore, the Spoken Language Processing Group has been actively involved in corpora development and evaluation, participating in evaluations organized by ARPA, the LE-SQALE project, and AUPELF-URE (Lamel et al., 1996).

D. Survey on language learning

Several national-level surveys have analysed students' language learning approaches in various environments. (Kojic-Sabo et al., 2002) analysed differences in independent vocabulary learning among students in ESL (English as a Second Language) and EFL (English as a Foreign Language) environments. The findings could inform language educators and policymakers about effective vocabulary learning strategies in different language learning contexts. Similarly, Al-Malki and Javid, (2018) used the BALLI (Beliefs about Language Learning Inventory) to study the impact of realistic beliefs on language learning. It highlighted the importance of fostering positive beliefs and attitudes among language learners, as negative notions can hinder the language learning process. Nair et al., (2021) explored the role of language learning strategies in autonomous learning among Malaysian primary school pupils. The study may provide insights into effective strategies for promoting autonomous language learning, particularly in the context of primary education.

E. Surveys on undergraduate students' interviews and employability in the Indian context

Several studies have explored aspects related to undergraduate student employability in India, such as students' perceptions of skill development (Jackson, 2013), employment predictors (Gokuladas, 2011), and career choice influences (Gokuladas, 2010). Additionally, research has looked at students' career outlook (Donald et al., 2018) and the effects of COVID-19 on education (Ahlawat, 2020). Though direct surveys on interview practices are sparse, these studies highlight the importance of understanding employability skills and career choices. This context underlines the benefit of AI-powered mock interview platforms to improve hiring processes. These platforms can provide valuable practice opportunities for students to enhance their interview skills and gain confidence in real-world job scenarios. The study by Krishna S and Karthika (2024) explores the efficacy of using podcasts tailored to learners' transportable identities in enhancing speaking proficiency among engineering undergraduates, shedding light on innovative approaches to language instruction. These podcasts could be integrated with digital avatars and drive the communication.

F. Surveys AI Powered Language Teaching and Learning Tools

Learners are having various options like Google Translate, Text to speech (TTS), English Able, Orai, Elsa, Chatbot, Duolingo, Neo platforms, etc to improve language proficiency. English Able is a assessment based learning environment for grammar. Orai is quite useful for public speaking. English Learning Speech Assitant (ELSA) is quite useful for pronunciation. Duolingo is designed for learning foreign languages and English. Neo is an integrated learning solution for English (Nur Fitria, 2021). Each of these tools specialized in multiple areas but there is a need to integrate and develop a holistic, comprehensive and exclusive English learning management tool powered by AI, covering AI driven speech evaluation, digital avatars with multiple accents, technical and business communication, presentation skills, productivity measurement, and AI agent communication.

3. Preventing Bias

Using specific age ranges, genders, and ethnicities in AI-based algorithms can lead to biased algorithmic outcomes (Hall & Ellis, 2023). The algorithms may establish a correlation between the selected attributes and the target variable, which could introduce bias into machine learning-generated results (Soleimani et al., 2021). Therefore, parameters that identify protected characteristics (such as age, gender, and ethnicity) should be avoided in AI-based algorithms to prevent the propagation of bias. Instead, AI algorithms should focus on relevant job-related attributes and skills to ensure fair and unbiased results. The proposed platform, thus focuses on the use of AI in following ways.

1. To assess candidates based on their skills and qualifications rather than personal characteristics, thereby reducing bias in the hiring process.

2. To evaluate pronunciation, intonation, written, and spoken grammar, technical correctness, and relevant job-specific knowledge and competencies.

3. To generate formative feedback, which helps candidates understand their strengths and areas for improvement.

Provide personalized interview questions based on the candidate's background and qualifications, ensuring a fair and relevant assessment process.

4. Design And Implementation

The design of the platform considered usage of AI as mentioned in the Section 3. Similarly, it also considered the following hypothesis before designing the product (skill2030.com).

A. Hypothesis

1. Communication skills gap prevent candidates to perform better in interviews despite having good domain understanding.

2. The education curriculum does not emphasize communication skills as part of instruction stream

3. Fear factor / social bias prevent exhibition of knowledge before interviewer

4. The Human Computer Interface (HCI) between a learning system and learner need to be more interactive and personal

There are several Learning Management System (LMS) available, yet none of them address these hypotheses in a holistic manner (Ülker and Yılmaz, 2016). Building on prior comparisons of Moodle and Blackboard, Subramanian et.al. (2014) study analyzes core functionalities to determine their relative strengths in promoting effective online learning. These platforms offer content management, forums, leaderboards, workflows, as well as ability to plugin with third party systems for various other tasks including spoken assessments. However, they are not dedicated systems for English Communication Skill training and assessments. Skill2030.com addresses above mentioned hypothesis with the help of AI, digital avatars with multiple accents, dedicated assessment engine for reading, listening, speaking, and writing skills as well as ability to do short answer grading using AI based techniques. It also has easy to use feature to conduct online automated interviews for thousands of candidates without any human intervention, making it an ideal platform to conduct this study. At the time of conducting this study, there was no other easily accessible platform that offered all the needed parameters.

B. Platform Features and Relevance

The key features of the platform are presented below.

- Real-time Feedback: Provide learners with real-time feedback on their performance and progress, both domain level and communication skills.
- Quick Access to Relevant Info: Ensure learners have quick and easy access to relevant course materials and resources, reducing barriers to learning.
- Metaverse Master Trainers (Indian Patent 433471 Granted): A unique interface involving digital humans who interact with the learner in real time both to present the content, as well as empathetically engage them in various activities. Figure X shows the 6 trainers the platform offers.
- Personalizes Learning: Utilize AI-based recommender systems to adapt the learning journey to the needs and preferences of each individual learner. Recommend learning activities tailored to their strengths and weaknesses.
- Automated Interviews: Allow for learners to take interviews on their chosen job roles and practice as they learn.
- Mentoring: Allow for mentors to create cohorts and mentor both individually and as a group by monitoring performance, personalized messaging and insightful dashboards.
- Learning Pathways: The platform offers tailor made and customized pathways for learners including basic engineering skills for freshmen, interview skills, and preliminary MBA courses.

C. Metaverse Trainers

As part of platform creation, six metaverse master trainers are created as showed in Figure 1. These avatars cut across three different accents like Indian, American and British and both genders. Authors received patent grant on "a method and system for real time rendering of a metaverse master trainer of an expert on a user device" (Indian Patent 433471) for these avatars creation. These AI Powered avatars are helpful in effective user engagement and fulfilment.

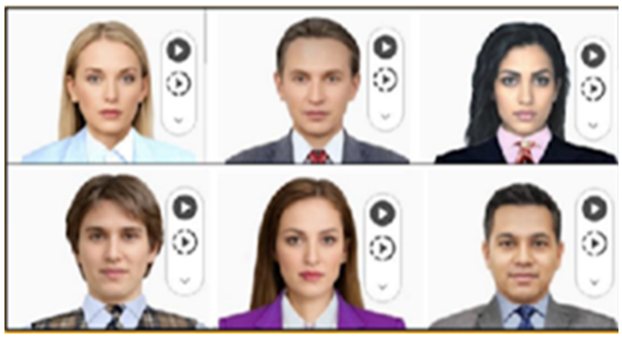

Fig. 1: Metaverse Master Trainers

D. Performance Indicators

Figure 2 presents the platform's robust performance analysis capabilities. It provides a holistic view of individual speech analytics by monitoring a comprehensive array of metrics, from basic progress indicators like Activities, Pathways and Enrolled Courses Completed, to nuanced language proficiencies including Pronunciation, Intonation, Speaking, Reading and Writing. In addition, it evaluates Comprehension, Domain Knowledge and Fluency, alongside more advanced measures like Syllable Stress and Spoken Grammar. The platform also analyzes writing quality at word and sentence levels, tracks grammatical and spelling errors and monitors performance over time. This multifaceted analysis empowers users to understand and improve their linguistic skills effectively.

Fig. 2 : Performance Analysis By Skill2030 (a) Overall Dashboard (b) Individual Activity

Additionally, the platform should improve the overall quality of the assessment, enhance the reliability of the data, and align with outcome-based educational goals (Pujari et al., 2024; Brindha, 2020)

E. Assessments

Phonetic Evaluation Engine for British, American & Indian English Combined, Automated Written Assessments Grammar, Vocab, Style, Technical + Semantic Correctness, etc assessment modules are developed as depicted in Figure 3.

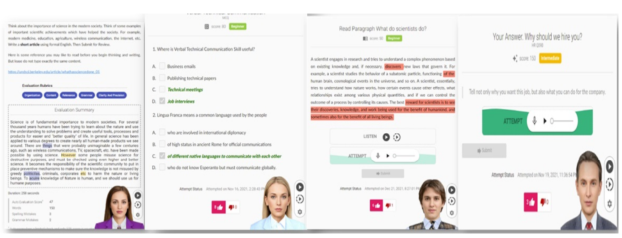

Fig. 3 : Various Assessment Modules. From Left To Right – Spelling And Grammar, Mcq, Listening And Spoken Skills and Subjective Answer Evaluation.

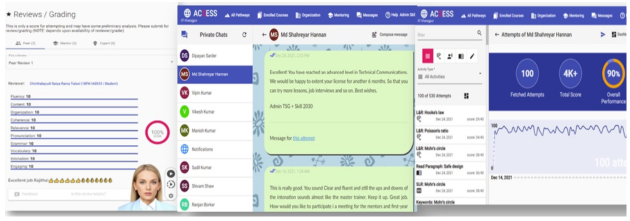

Fig. 4: Reviews, Mentor-Mentee Chatting, Student Dashboards

Figure 4 illustrates other aspects of the system like Peer / Mentor / Expert reviews with Alumni Engagement (left), Private Learner-Mentor Chat (middle), and Flexible Student Dashboards depicted (right).

5. Methodology

Authors have adopted the survey method of quantitative research by designing a structured instrument (questionnaire) which was to be virtually answered by individuals, chosen from different backgrounds and geographical locations involving large sample sizes. The primary goal of the instrument design was to assess individual student's basic employability skills, with the following broad objectives:

1. To assess student's individual ability to respond to basic self-introduction-based questions.

2. To evaluate individual ability to converse for job specific questions.

3. To understand individual ability to converse and respond to domain specific questions

The instrument (questionnaire) was designed to proceed in an orderly and specific manner, and in order to take care of the ambiguities and inflexibilities in questions, feedback and comments were received from pilot samples and the said questions were restructured, so that authors could arrive at the instrument for assessment.

Figure 5 shows the flow chart of instrument design and the various steps adopted in arriving at the final structured instrument for research. Each item in the flow chart depend upon the successful completion of all the previous items. It may be noted that there are two feedback loops in the flow chart to allow revisions to the methodology and instruments. The final survey instrument, consisting of 76 questions covering various aspects, underwent refinement during three

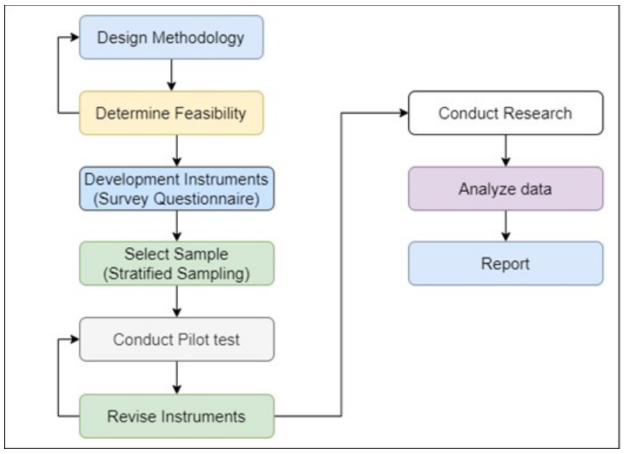

Fig. 5 : Flow Chart Depicting the Steps Taken for the Design of the Structured Instrument and Subsequent Research

phases. The survey was administered to undergraduate engineering college students across India, encompassing all 27 states, over a duration of eight months. Various methods, including All India Council for Technical Education (AICTE) partnership (a national-level Apex Advisory Body to manage technical education in India), were utilized to reach out to colleges voluntarily. A total of 998 colleges participated in the assessment.

A. Mock Interview Platform and Survey Participation

The AI-driven, mock interview automation platform, Skill2030.com, ensures impartiality towards the candidates' financial, social, or demographic status. It generates random questions stemming from the candidate's educational domain and career interest field, ensuring a level playing field for all users.

Participant Statistics

- Total Students Registered: 17,317
- Total Interviews Conducted: 6,619

A total of 826 students from Tier 1 colleges, including IITs and NITs, along with 3,209 students from Tier 2 colleges, such as IIITs and prestigious Deemed Universities, participated in the assessment, as illustrated in Figure 2. Additionally, 13,282 students from Tier 3 colleges registered for the assessment as presented in Figure 6. Users had the opportunity to enhance their performance by reviewing the feedback provided for their assessments and focusing on areas that require improvement.

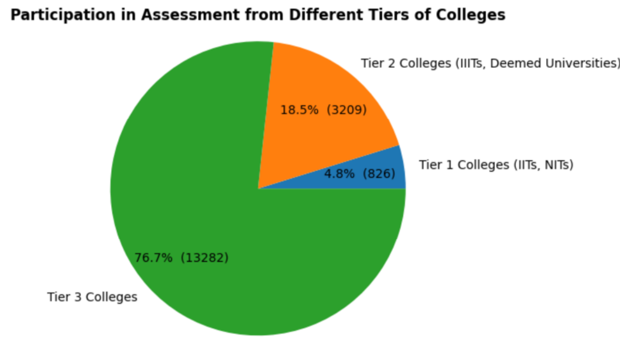

Fig.6 : Registered Student Distribution Across Various Types Of Colleges

Figure 7 shows the distribution of students according to their study background, majority of the students are from computer science background followed by electronics and electrical.

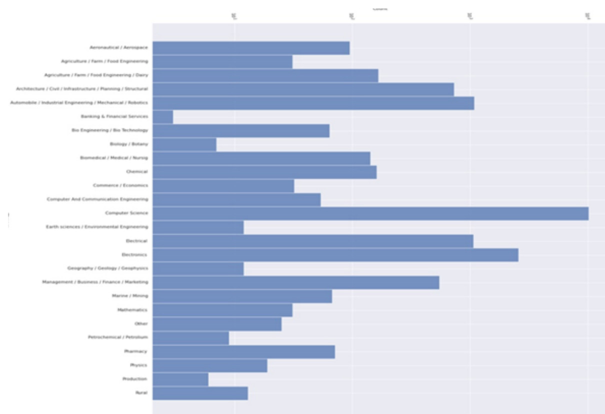

Fig.7 : Student Educational Background

B. Key Variables

The individual's ability to handle a job interview was assessed through various parameters, including speed, fluency, writing, speaking, listening, intonation, comprehension, pronunciation, spoken grammar, written grammar, domain knowledge, spoken word quality, written word quality, spoken sentence quality, written sentence quality, and domain-specific terminologies.

The questions in the portal are created based upon the various companies interview questions available on the internet from domains like HR/General, CSE, Electrical, Electronics, Civil, Mechanical, Chemistry, Physics, Mathematics.

C. Analysis of the Responses

The HR and general questions encompass commonly inquired topics such as self-introduction, strengths, and career goals. The computer science and engineering (CSE) related questions focus on contemporary technologies and tools relevant to software engineering careers, including GitHub, programming, networking fundamentals, data structures, databases, and advanced topics like Natural Language Processing (NLP). For students with backgrounds in electronics, the questions cover areas such as Internet of Things (IoT), logic gates, and transistors. Electrical questions delve into Electric Vehicle (EV) motors and power diodes. In the field of civil engineering, the questions revolve around design parameters for structures and reinforced concrete, among others. Figure 8 depicts the correlation among the above parameters from the student attempts. Following are the key observations:

1. Listening and comprehension exhibit a positive correlation. This makes logical sense, as the better one's listening skills, the better their comprehension of the information being conveyed. Essentially, as one improves, so does the other.

2. Pronunciation and speaking demonstrating a positive correlation indicate that as a person's pronunciation becomes more accurate, their overall speaking ability improves. This suggests that accurate pronunciation is a key component of effective speaking.

3. Spoken sentence quality and spoken grammar have a negative correlation in the studied data. The sentence quality is evaluated based on an optimal average of 17 words per sentence. However, longer sentences, judged as 'high quality' by this measure, tend to have more grammatical errors due to their complexity. Shorter sentences, on the other hand, though deemed 'lower quality,' are generally more grammatically correct due to their simplicity. This highlights the complex dynamics between sentence length, quality, and grammar accuracy in spoken language evaluation.

4. The negative correlation between intonation and speed is explainable as when one increases their speaking speed, maintaining proper intonation becomes challenging. Therefore, quick speech often comes at the cost of varied and effective intonation.

5. Lastly, the negative correlation between intonation and spoken sentence quality suggests that putting an emphasis on varied intonation may actually negatively impact other factors considered in 'sentence quality' such as sentence length and structure. This could be because focusing on intonation might cause the speaker to use simpler or shorter sentences to more effectively vary their pitch.

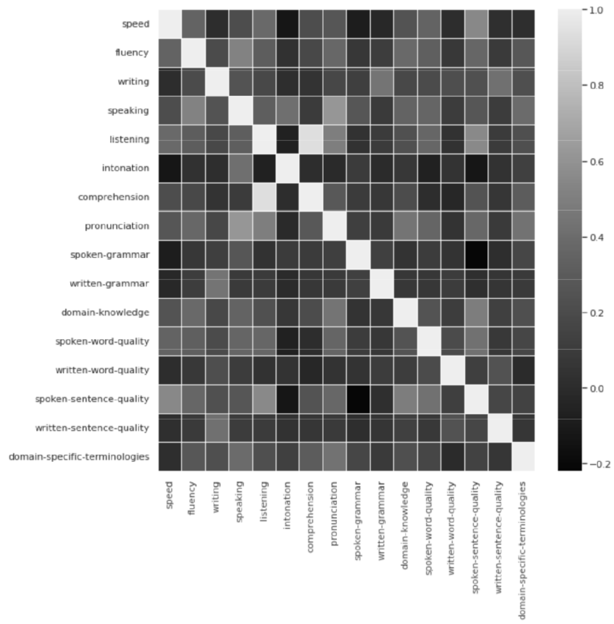

Fig. 8 : Heatmap On All Parameters On All Questions

Figure 9 presents boxplots for some of the parameters discussed earlier. The boxplot reinforces the five observations mentioned earlier. Additionally, it was found that candidates showed good performance in spoken grammar but struggled notably with intonation. Other skills, such as listening, speed, comprehension, and written grammar, were moderately well-developed, whereas speaking, pronunciation, and fluency were areas of relative weakness.

This trend might suggest that while candidates are able to comprehend and listen efficiently, possibly due to an educational focus on these skills, pronunciation and intonation might be getting less emphasis in their training. It's likely that a potential disconnect between comprehensive communication skill training within the curriculum and these specific areas of weakness exists. However, this hypothesis needs to be investigated further, and it's essential to also consider alternative explanations. For instance, the observed patterns may be specific to the candidates assessed in this study, or they might reflect larger trends in education and training more generally.

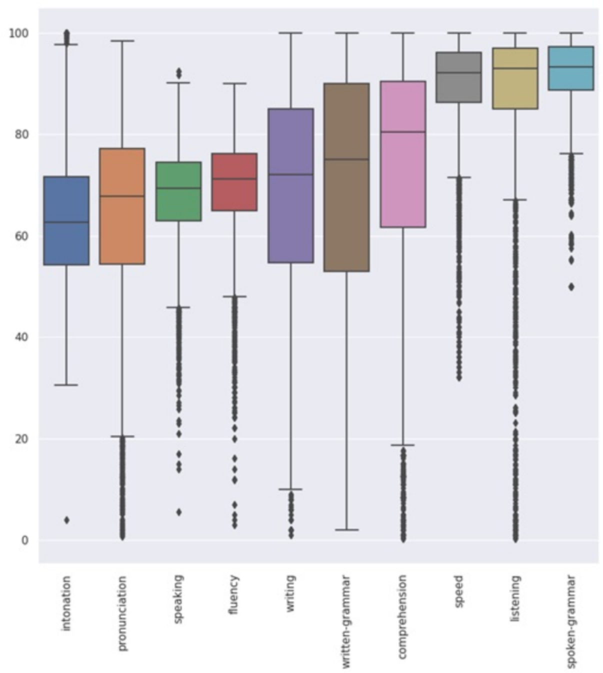

Fig.9 : Boxplot Of Evaluated Scores for Various Parameters

D. Mock Interview Feedback of 1460 Users Across India

Authors collected subjective feedback and did a sentiment analysis (Bhoi & Thakkar, 2022) (Figure 10) and topic modelling using LDA (Latent Dirichlet Allocation) (Blei, Ng, & Jordan, 2003) (Figure 11), NMF (Non-Negative Matrix Factorization) (Popov, 2023) (Figure 12), and BERT (Bidirectional Encoder Representations from Transformers) base model (Devlin et al., 2019).

Based on the analysis of 1460 users across India, the mock interview feedback on the AI-based platform indicated overall positive sentiment as showed in Figure 10. In this study, authors leveraged the TextBlob, a popular Python library for processing textual data, to conduct sentiment analysis. TextBlob includes an API that is built on top of the implementations of Naive Bayes Analyzer and Pattern Analyzer, which are capable of determining the polarity and subjectivity of a piece of text. The polarity score is a float that lies within the range [-1.0, 1.0], where 1.0 indicates a high level of positivity and -1.0 indicates a high level of negativity.

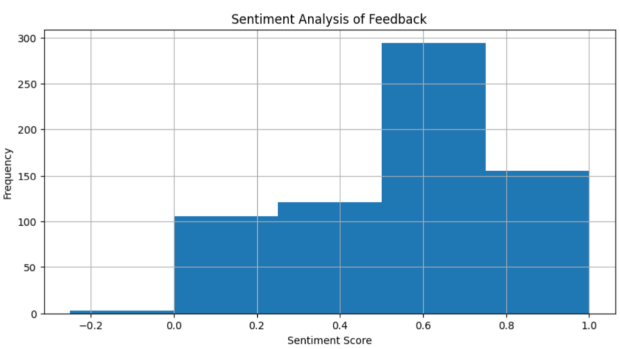

Fig. 10 : Sentiment Analysis

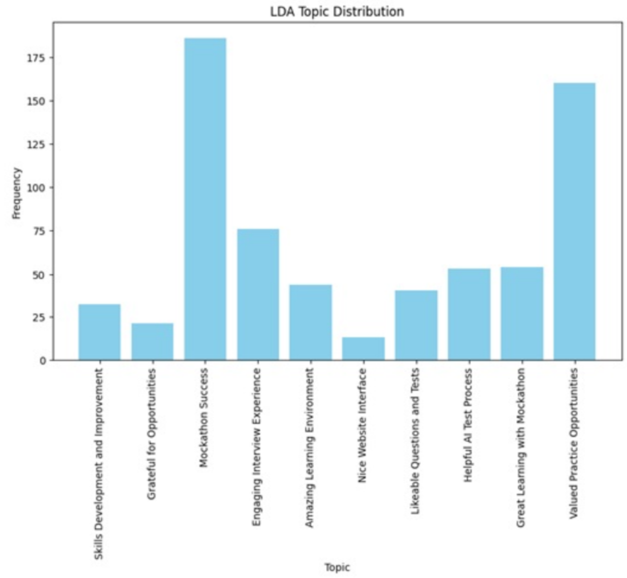

Fig.11 : LDA Topic Distribution

LDA Topic distribution gives highest frequency to Mockathon overall success, valued practice opportunities, etc.

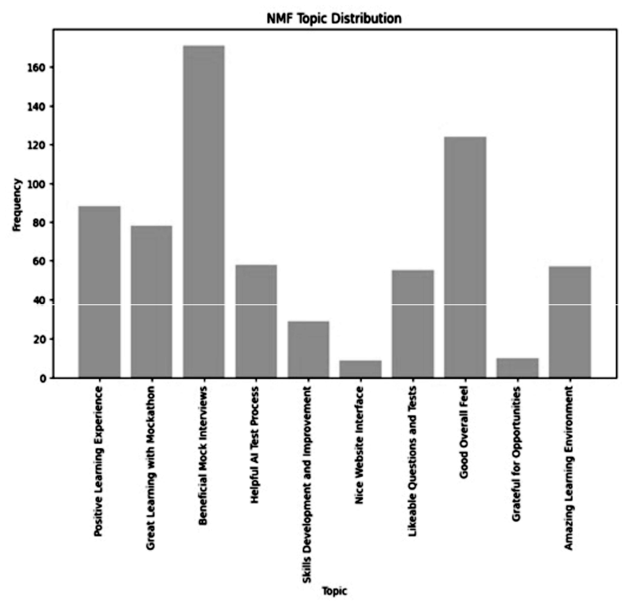

Fig.12. NMF Topic Distribution

Authors also used sentiment analysis technique combining transformer-based embeddings with unsupervised clustering and predefined sentiment classification models. Initial text encoding is performed using DistilBERT, a lighter version of BERT, which generates contextual token embeddings. The average of these embeddings is computed to obtain succinct document representations. Subsequently, the MiniBatchKMeans algorithm, a variant of the K-Means clustering method, clustering these document embedding vectors into predefined numbers of topics. Lastly, the sentiment-analysis pipeline from Hugging Face's transformers library classifies the sentiments of the texts as 'Positive' or 'Negative'. This compound procedure allows for an efficient and effective sentiment analysis, providing insight into not only the sentiment but also the thematic content of the texts. It was received 98.5% positive feedback. Rest gave constructive comments. This overall experience is presented in Figure 13.

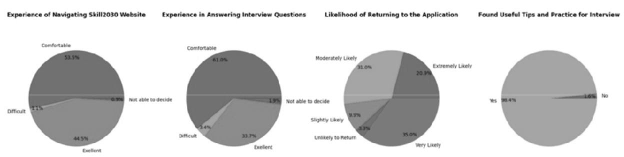

Fig. 13 : Overall Experience

E. Impact Analysis

In this study, further engagement was observed from numerous participants on the Skill2030 platform which has been systematically designed to enhance technical communication skills. The course structure commences with rudimentary tasks, progressively escalating to more complex concepts. A close examination of 500 users who have attempted at least 70 questions or more over a span of 6 months offers valuable insights into their cumulative performance trajectory as showed in Figure 14.

Authors observation revealed the following trends:

- Correctness initially drops from 86% to 82% as the difficulty of questions increases. However, after approximately 200 attempts, it consistently rises and reaches a peak of 96% after 400 attempts.

- Pronunciation starts at a moderate 60% but decreases to 53% after 300 attempts. Interestingly, with further practice, it changes dramatically. Pronunciation scores sharply increase, reaching 83% after 480 attempts.

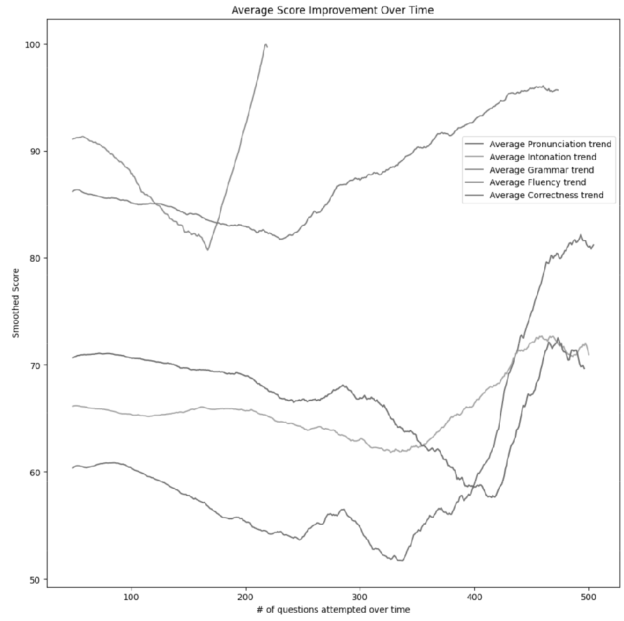

Fig.14: Average Score Improvement Over Time

- Intonation starts at 66% and shows a minor decline to 63% with 300 attempts. Despite this initial drop, it gradually increases with further practice, reaching a moderate 73% after 450 attempts.

- Fluency starts relatively high at 72%, but gradually decreases to 67% after 300 attempts. There is a significant decline to 58% around the 400-attempt mark, as learners focus more on pronunciation and intonation. However, after a dip, fluency sees a sharp rise, reaching a commendable 74% after 470 attempts.

Written grammar reveals an interesting pattern - it initially decreases from 90% to 80%, but bounces back effectively after Approximately 150 attempts and climbs to a high of over 95% after 220 attempts.

The data reveals a conceivable pattern. There is a clear divide between grammar and correctness vs the spoken skills as people struggled more in spoken skills than those skills which are readily taught as part of the curriculum. Also, students fairly adapt to straightforward tasks when initiating the curriculum, but as the intricacy of the exercises increases, a marginal decrease in performance is recorded. Nonetheless, persistent practice and accumulating experience led to a gradual enhancement in their performance. Notably, the growth in understanding technical concepts and grammatical facets tended to be significantly faster compared to developing key communication components such as pronunciation, fluency, and intonation. Especially, intonation was found to be the most challenging aspect to ameliorate, indicating the need for more focused practice. An in-depth study of a cohort of students who devoted additional time for practice clearly implied a correlation between the amount of practice and improvement in their skills. This is visible clearly for those who attempted more than 350 questions. Another interesting fact to observe is how as students learn to pronounce and use proper intonation, fluency takes a hit, but as they practice and get used to, they pick up in fluency as well. Fluency may seem to have improved by only 2% but initially candidates were fluent with bad pronunciation, intonation and grammar, however they improved in all those aspects significantly and also learnt to be slightly more fluent with those accompaniments.

Conclusion

In conclusion, this study unveils the substantial benefits of AI-powered, real-time mock interviews in enhancing jobseeker preparation. The AI-driven evaluations serve as a pivotal tool for bolstering communication skills, providing candidates with consistent, personalized practice and feedback in a flexible, accessible format. Moreover, the importance of intertwining a systematic learning approach with communication skill assessments is underscored through substantial improvements in sentence quality, fear reduction, and overall performance.

Further, the standout potential of interactive digital human trainers in the AI-based platform was observed, marking its potential effectiveness in increasing engagement and imparting a realistic interview experience. This amalgamation of innovative technology and pedagogical principles fosters a comprehensive and holistic preparation strategy, setting candidates up for success in a competitive job market. In essence, this study serves as a testament to the transformative potential of such platforms in shaping the future of job interview preparation and how they can become an integral part of the hiring landscape for forward-thinking companies looking to optimize their recruitment processes.

Future Work

The future work entails establishing relationships between candidates' Intelligence Quotient (IQ), Emotional Quotient (EQ), Social Quotient (SQ), Adversity Quotient (AQ) and interview performance. This will encompass assessing cognitive abilities (IQ) and relating it to adaptability potential, gauging emotional intelligence (EQ) to predict teamwork and job satisfaction, evaluating social competence (SQ) to measure communication effectiveness, and examining resilience (AQ) to ascertain an individual's capacity to cope with adversity. Accordingly, strategies for improvement that include mental challenges, empathy training, active listening exercises and resilience-building activities would be recommended for candidates scoring lower in respective quotients. This multi-dimensional approach could be a potential game-changer in refining comprehensive candidate assessments.

As the research progresses, there is a keen interest in investigating the intricate role of confidence in interview performances. Bridging the gap between various language proficiency parameters and individual confidence levels, diverse aspects will be explored. These aspects range from the influence of confidence on speaking fluency and writing precision to its effect on active listening and accurate comprehension. The impact of confidence on the quality of spoken and written words, the structure of sentences, pronunciation and intonation, usage of grammar, and domain-specific terminologies will be delved into. A preliminary review of student feedback indicates significant confidence boosts from the mock interviews – a promising indication of the future potential of exploratory work in this domain.

Additionally, the efficacy of Metaverse Master Trainers will be evaluated through a multi-faceted strategy. Initially, user-centric surveys and interviews will be conducted to garner feedback regarding the engagement and effectiveness of these Master Trainers. Simultaneously, intrinsic AI capabilities will be utilized to analyze user progression and performance data. This layered strategy will gain further solidity by incorporating A/B testing. Users will be divided into two categories; one will access the Metaverse Master Trainers while the other will proceed without them. By comparing the progress and performance of these two groups, the impact of the trainers will be analyzed in a quantifiable manner. Cross-referencing insights from user feedback and statistical findings from AI-based and A/B test analysis will offer a comprehensive understanding of the role of Metaverse Master Trainers within the platform.

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