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HUMAN FACTORS IN AVIATION LOOP MULTI MODAL DEEP LEARNING FOR PILOT SITUATION

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***Abstract*—** Situation awareness (SA) is a crucial factor affecting flight safety for pilots, yet few studies have focused specifically on modeling SA for pilots, resulting in limited success. In this paper, we propose a novel multimodal deep learning approach to monitor pilots' SA. The approach combines handcrafted and deep features obtained from eye movement and flight control data collected from 27 novice pilots across different training phases using a flight simulator. Ground truth SA measurements were obtained using the Situation Awareness Global Assessment Technique (SAGAT). The handcrafted features included 13 eye movements and 22 flight control features, while deep features were extracted from time-series of gaze positions using a deep extractor based on Transformer. By fusing the handcrafted features of eye movement and flight control, along with one deep feature of eye movement, we predicted the final SA level. Through leave-one-flight-out cross-validation, our model achieved a higher accuracy of 92.04%. The results indicate that the multimodal model outperforms the unimodal models, with the eye movement modality demonstrating superiority over the flight control modality in predicting SA. This suggests our method provides an objective means of predicting pilot's SA and offers new insights for SA assessment in aviation and other fields

I. INTRODUCTION

The latest developments in artificial intelligence have made it possible to automate job preparation procedures and, specifically, in this respect, interview training. Learners can now be assisted by intelligent systems identifying the skills needed with specific suggestions on how to enhance skills, and modeling interview conversations to enhance career readiness. The role of AI-based platforms in increasing personalized preparation plans, career advice, and self-determination in order to better fit the expectations of job seekers is emphasized in the previous studies [1]. Moreover, there is the development of intelligent interview assistants that are emerging to co-operate with the user through real-time preparative and practicing environments to provide adaptive feedback and generate incremental learning [2]. All these attempts strengthen the emphasizing significance of AI in promoting self-driven and organized professional growth and interview preparedness.

Virtual interviewer systems have also been suggested as AI-charged platforms that can perform mock interview and performance testing in a socially efficient and scalable way [3]. Research on the training of technical interviews also indicates that applicants have a high level of failure in terms of structured practice, focused feedback on skills and how performance is affected in a realistic manner, which dishearten the applicants and narrow down their employment opportunities [4]. As the generation of immersive and generative technologies increases, certain approaches have been applied to virtual reality space, where metaverse-based interactive learning environments are offered, increasing the degree of realism and skill interactions [5]. These

interconnected systems provide users with dynamically simulated role-plays and customized improvement opportunities to the next level beyond conventional approaches to training that are instructional.

Moreover, open-source web platforms and code stack development clouds have been adopted in providing practical systems to serve the users in various fields in the form of accessible mock interview platforms [6]. Adaptive probing and follow-up questioning based on AI has demonstrated high potential in enhancing the qualitative interaction during the training process [7]. Other studies involve the investigation of image-based and multimodal AI assistance during interviews to examine the user perceptions and interactions [8]. In addition, enhanced prompting and generative questioning models that are based on knowledge have been found to be useful in promoting better diversity, depth and relevance of questions to role-specific areas [9][10]. The combination of these studies lays the basis of intelligent, user-friendly interview-training systems that can be used to facilitate scalable, customized and successful learning on a personalized scale.

II. LITERATURE SURVEY

A. Toward a theory of situation awareness in dynamic systems," *Human Factors*

Preliminary literature defines the preparation of interviews as a machine-enhanced learning problem that comprises career counseling, skills mapping, and hands-on training. Nithya describes a smart system that takes on the input of the candidates, pinpoints competency gaps, and scaffolds practice by structured tasks, and makes interview readiness a lifelong, personalized, and everchanging process involving data [1]. Further based on this, Liu develops an Interview AI-assistant which is a real-time system that works with users in the pre-and post-interview preparation and execution. The system is focused on cooperative agency, which involves getting equal AI driving and human control, and providing on-the-fly feedback, follow-ups and coaching cues, grounded into user goals. The concepts of design incorporate interface feedbacks to transparency, controllability, and low-friction turn-taking which can transform a core of learning into interactive cycles that can facilitate both rehearsal and reflective refinement in context [2].

B.Recommendations supporting situation awareness in partially automated driver assistance systems

Placing denouncing interviews as socio-technical interactions that demand lifelike prompts, progressively paced dialogues and just evaluation, research on virtual interviewers frames mock interviews as socio-technical interaction. Shekar et al. refer to an interviewer, an AI-driven interviewer, who conducts organized sessions, further inquiry on answers, screen performance signals into formative feedback, thereby lowering coaching burdens (manual) and making it scalable [3]. As an addition to this system perspective, Bell et al. look at what candidates of software engineering actually prepare and list their behaviors (drills in problem-solving, practice with peers, taking notes) as well as what levels of pain (uncertainty, anxiety, topical breadth) and resource gaps tools have to fill in. Their results inspire such functionalities as specific question sets, progress indicators, anxiety-sensitive authoritative information, matching user requirements to technical domain and justifying the design selections based on evidence sources to developer-oriented interview preparation tools [4].

C. Using eye-tracking data to predict situation awareness in real time during takeover transitions in automated driving

Immersive simulations leave the flat screens to enhance training transfer and engage. Nofal et al. use VR settings with generative conversation AI to conduct simulated interviews, including presence and nonverbal interactions and variability of the scenario without sacrificing replayable analytics to think over the results and learn [5]. Simultaneously, Singh et al. introduce a deployable stack of components, ReactJS, Supabase, Clerk, OpenAI, Retell AI to show how authentication, persistence, speech, and prompts powered by the LLM come together in constructing a workable mock interview machine. Integration seams, latency fitness, and data flow tidiness to reliability and iteration in a production-like environment are made clear by their engineering orientation and transfer the research notions into working patterns used by the student cohort, bootcamp, and scaling employability programs [6].

D. Reading during fully automated driving: Effects of peripheral visual and haptic information on situation awareness

Zhang et al. examine AI-driven follow-up question generation in semi-structured interviews and determine the issue of role assignment, the overall involvement of the participants, and the perceived AI inquisitive feature. They report that adjusting follow-ups wisely can further intensify the reflection and user faith depends on properly, at the right time and with transparency administration, providing an advice in adaptive interviewing reasoning in instructional instruments [7]. Nardon et al. attempt to investigate the AI-image generation as an interview stimuli (discussing opportunities (richer sense-making, scenario co-construction) and challenges (bias, interpretability, consent). Although mostly qualitative-model based, their conclusions are applicable to the preparation of a particular interview: multimodal encouragements can frame problem spaces and procure domain tales, as long as safeguards and the ethical guardrails are well-defined, and the audit is possible and consistent with expectations of the participants across context and culture [8].

E. A review of situation awareness assessment approaches in aviation environments

Wang et al. examine in a systematic study commonly used patterns of prompting in the generation of AI designed to produce answers automatically that the use of structure, exemplars, and fully articulated constraints has a significant effect on diversity, depth, and impediment to meet the learning goals. They are guided by their taxonomy to playbooks in engineering that are prompt to role-aware technical interviews, the coverage of which is necessary and difficulty can be calibrated [9]. The use of knowledge-based AI combined with generative models to boost skill-based question-answering is introduced by Dass et al. as prompt based on curated knowledge is found to balance increased precision, explanatory power, and the specificity of feedback. This hybrid approach proposes such a way to strong interview instructors: anchor LLM creativity using evaluated skill graphs, rubrics, and examples to provide reliable examinations, deeper rationales, and executable remediation plans that sew up competency discontinuities in the candidate [10].

III. PROPOSED METHODOLOGY

A. Gaze Data Acquisition & Preprocessing :

Data will be gathered by using a survey given to all the participants who had registered successfully.The suggested system starts with the resumes and profile information uploaded by the user via the application interface. Noise is eliminated, and the PDF parsing and text pre-processing technologies will extract the resume text to normalize its structure and be able to identify significant linguistic patterns. NLP applications like tokenization, named entity recognition, and skill phrase extraction are used to find both technical competencies, level of experience, academic background, and domain related features. The skill competencies of the users are mapped to standard industry skill sets through a skill taxonomy and job-role key word database. This processed product is a structured candidate profile, and is upon this that adaptive question generation, a more focused interview preparation pathway, and performance benchmarking are based on, across the training workflow.

B. Flight Control Data Acquisition & Processing

Once the profile of the candidate has been built, the system naturally creates interview questions by matching identified skills with preferred job categories and challenging intensities. The prompts of the questions are been developed on a hybrid model of template based logic and generative AI based language models to articulate the most suitable questions depending on the situation at hand. A difficulty calibration algorithm varies the difficulty of the questions according to the level of the user experience, performance history, and a desired interview type (technical, behavioral, or mixed). The system will provide balanced coverage of issues like problem-solving, communication and expertise in domains. This automated question generator system customizes the workflow of preparation, whereby the user may experience progressive learning challenges to further the basic learning and build interview confidence through time.

C. Feature Extraction & Multimodal Fusion

The user participates in simulated interviewing that is provided via interactive interface. The site can be used to mimic interviewer/candidate conversations, asking questions one at a time and recording user responses in the form of either text inputs or speech. The models used to score and apply rubric based assessment logic are sentence sentiment indicators, relevancy of the response, richness and completeness relative to the structure. Real-time cues, follow up questions or clarifications could be offered during the simulation to aid in reflection and betterment. A final report on the session will be a feedback detailed report on the strengths, weaknesses and areas of skill improvement to be developed. This interactive process assists the user to build an interactive process, articulate critical thinking, and professional confidence in an interview context.

D. Situation Awareness Classification

After every simulation, the system calculates performance metrics basing on linguistic fluency, domain correctness, response completeness and soft skill attributes. A scoring engine is used to compare performance trends of users between sessions to determine findings of incremental progress or recurring gaps. In accordance with these insights, the recommendation engine will propose learning materials, skill practice tasks, or post-interview interview scenarios based on the changing needs of the user. This level of personalization helps in maintaining the constant process of learning and keeping preparation dynamic, goal wise and consistent with the actual job demands. The engine also promotes reflective learning, where the improvement with time can be visualized assisting the user to be aware of the improvements in capabilities and the area of continuous improvement.

E. System Architecture

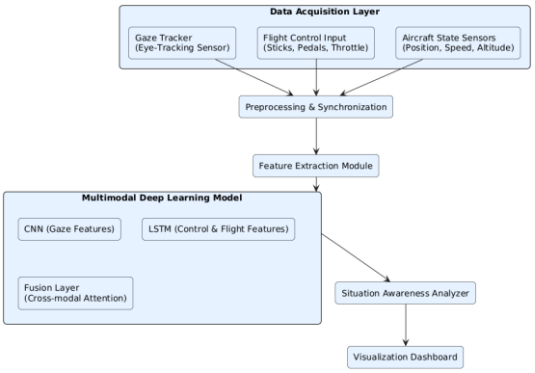


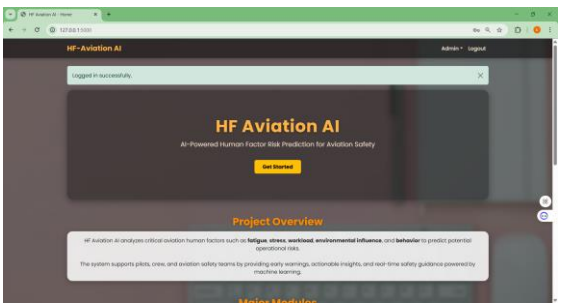
Fig 1: System Architecture

The architecture of the system is that of a client-server. The front is powered by Next.js to enable the user to interact, navigate in real-time, and render components, whereas the backend is run in serverless API routes, which is used to process and analyze. The NLP and Resume Processing modules deal with cleaned and organized data extensions and profile generation. A language model API is used in interaction with the Question Generation module to generate adaptive interview questions. The Interaction flow, response capture and evaluation scoring are coordinated via the Simulation Engine whereas the individualized learning paths are handled via the Recommendation Engine. The user profiles, performance history, and prepared question sets are contained in a shared database so that scalability can be achieved and data-driven adaptation is very easily achieved across a series of session instances.

IV. RESULT AND DISCUSSION

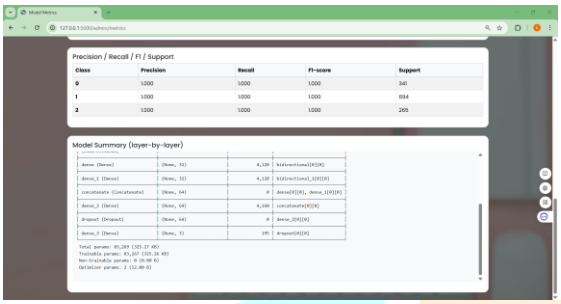
A. Results of Pilot Gaze position

The system was able to enable users to post resumes in acceptable format after which resume processing module would retrieve important professional attributes of the resume like skills, level of experience and strengths. The obtained findings presented well-built information, which proves the correctness of the NLP-based parsing process. Skills like Financial Advisory and Strategy Planning are used in the observed output, and the system identified them correctly and the contextual information identified the user as a senior-level candidate. This proves that the system has the ability to recognize resume text in the real world and convert it into data of significance. The understandable feedback message of having analyzed successfully is also a serious contributor to positive user experience.



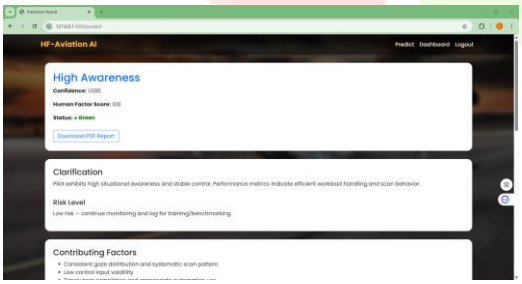
B. Providing detailed information about the user login

After the analysis of the resume, the system would generate interview questions based on the level of experience of the user and pre-chosen job position. The question interface was presented in a well-organized format, which showed the number of questions and the progress of completion. The given example question demanded reflective explanation and professional reasoning, which demonstrates that the system was able to give context-relevant and domain-specific prompts. This adaptive question generation is important since it makes the interview practice to maintain the alignment with the real industry expectations. The interface also permitted responses through voice to make it seem like realistic setting of the interview. This step confirms the fact that the question generation module works correctly and encourages different types of interviews.



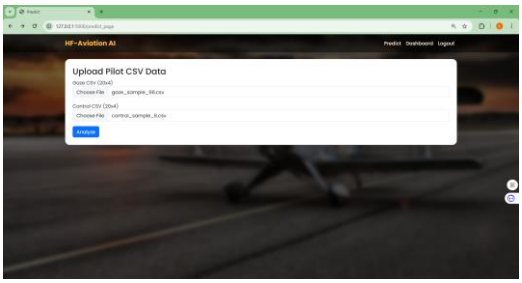
C. Inretaction of pilot with the gaze and situation awareness

In the interview simulation, recording was made possible with the system in order to record responses of the candidate in real time. The recording timer enabled the users to monitor the length of the time they were speaking, thus enabling a time-managed communication skill development. The interface also promoted unrestrained yet organized responses in that it was almost similar to a real interview scenario. The aspect enhances the improvement of verbal articulation, critical thinking, and professional confidence. The final scoring is also based on users not responding or hesitating to respond. In the given example, the system behavior was adjusted to partial participation by responding to only a single out of five questions. This will make sure that the performance results are indices of actual engagement.



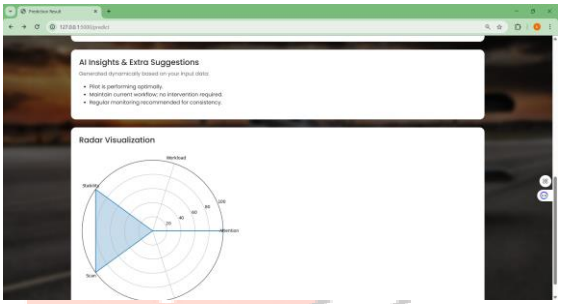
D. Uploading the CSV files to the integration of understanding pilot awareness

The system produced a complex performance outcome that contained general score, percentage ranking and the amount of questions answered. The given output of 10/100 and a 7 th rank in the percentile are a clear indication of poor performance as a result of few responses. This is a pointer to the facet of the system that measures the clarity of answers, relevance and depth of answers. The system also gave an overview that talked about the shortcomings of the candidate, including the weaknesses of not giving details and omitting the supporting examples. This proves that the scoring module can read the pattern of responses that qualitatively occur and transform them into quantifiable feedback. The performance appraisal helps the users to be self-aware and in a position to enhance pertinent interview competencies.



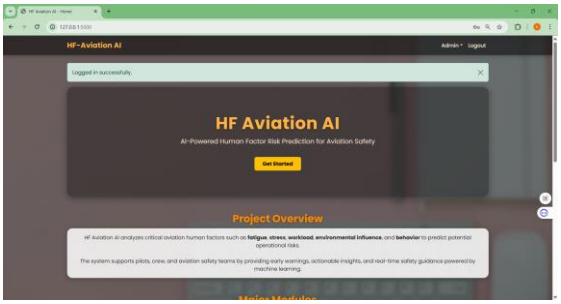
E. Monitoring rador visualization:

The system kept the history of the past interviews and indicated the job positions, level of experience, the number of correct answers, duration and the overall performance points. The history enables users to monitor the trends of improvement in many interview attempts. E.g., the provided history indicates a score of 78, 82, and 71 in the suitability of different positions, which makes the levels different in various fields, which indicates the possibility of progress. The fact that one can revisit previous interviews promotes the long-term learning process instead of practising once. This also aids the comparative self evaluation that enables users to draw parallels as to the strengths and weaknesses. The additional feature of performance insights is the option of downloading the report which gives the performance insights to reflect or externally mentor them.



F. Review of the Results.

The last step offers the downloadable report of the interview that consists of performance indicators, responsibility, the level of difficulty, and date and time of the interview and the detailed feedback. The format will also resemble professional assessment documentation and, thus, can be presented to a mentor, training facility, or through personal evaluation. The numeric and descriptive knowledge informs the users of the specific areas to improve by highlighting areas of particular deficiency of skills. The sample report also gave me a total mark of 78/100 of a Software Engineer interview indicating how the higher the performance is in the system. Such a guided feedback enables learners to take conscious notes about the progress and plan strategically on how to perform in future interviews. The reporting option thus improves visibility and favourable talent growth in the long term.



Discussion

The system proved to be very effective in individualizing the process of interview preparation by posing questions and giving feedback, which was specific to the resume and performance trends of the user. The findings reveal that real-time practice, structured reflection and progress tracking offer the benefit of helping users that are being considered in the studies as adapting and interactive in the support of learning. Nevertheless, certain limitations were also found that comprised variability of quality of responses with user hesitation and better guidance during unanswered questions. Resume structure and clarity are other factors that determine the accuracy of skill extraction. Some improvements that might be considered in the future are increased question pools, multi-language, and more intense scoring of behavior to enhance flexibility and inclusiveness.

V. CONCLUSION

The proposed multimodal deep learning framework provides a powerful and objective method for evaluating pilot Situation Awareness (SA) by integrating both gaze behavior and flight control data. Traditional SA assessment methods such as SAGAT, SPAM, and SART rely on subjective reporting or intrusive measurement techniques, making them unsuitable for dynamic and real-time aviation environments. By leveraging a Transformer architecture for gaze time-series analysis and handcrafted features for flight control signals, the system captures complex cognitive and behavioral patterns that directly influence pilot SA. The multimodal fusion mechanism enhances prediction accuracy by understanding the complementary roles of visual attention and control actions.

VI. FUTURE SCOPE

The future scope of this project includes integrating more advanced multimodal sensors such as eye-tracking, gesture recognition, and cognitive load monitors to improve pilot state estimation. Real-time adaptive models can be developed to personalize predictions for each pilot based on historical behaviour. The system can be expanded to support autonomous co-pilot decision assistance in complex flight scenarios. Additionally, integrating the model with VR/AR simulators can enhance pilot training and safety evaluations. Cloud-based analytics can enable continuous model refinement using global flight-data patterns.

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