PREPMASTER: A COMPREHENSIVE WEB APPLICATION FOR ENHANCING INTERVIEW PREPAREDNESS

Project Id: 24-25J-082

Final Report

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Dissertation submitted in partial fulfilment of the requirements for the Bachelor of Science (Hons) in Information Technology Specialized in Information Technology

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DECLARATION

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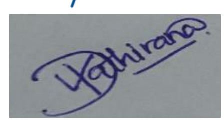
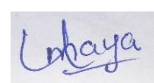
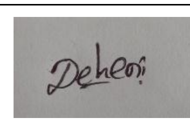
Pathirana V.P.E.P.V.	IT21175084	
Sathkumara S.M.P.U.	IT21306136	
Kavindya N.D.D.	IT21231278	

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ABSTRACT

This final report presents an integrated, AI-driven interview preparation platform comprising four interlinked components designed to enhance career readiness for IT professionals. The platform combines Natural Language Processing (NLP), Machine Learning (ML), and adaptive learning frameworks to deliver a personalized, interactive, and effective learning experience.

The AI-Powered Career Path Guidance System analyzes user resumes using NLP to identify skill gaps against targeted IT roles and generates individualized learning plans. It continuously updates user progress and achievements while supporting automated CV generation based on newly acquired competencies.

The Intelligent Video and Tutorial Recommendation (IVTR) System utilizes a hybrid ensemble of Random Forests, Decision Trees, and Artificial Neural Networks to deliver tailored learning content. The system dynamically adjusts to user behavior and performance metrics, significantly improving engagement and knowledge retention.

The MCQ Level-Up System offers an adaptive skill enhancement experience through progressively challenging multiple-choice questions. By integrating Item Response Theory (IRT) and Deep Q-Networks (DQN) within the Zone of Proximal Development (ZPD) framework, it ensures accurate skill estimation and optimized learning paths for roles such as Software Engineer, QA Engineer, and Project Manager.

The 2D Interview Panel Simulation System modernizes traditional mock interviews using real-time NLP techniques, including BERT-based semantic analysis, cosine similarity, and TF-IDF vectorization. It provides interactive, domain-specific simulations with dynamic feedback, fostering spontaneous thinking and improving soft skills through bidirectional communication with 2D avatars.

Collectively, these components deliver a comprehensive, scalable, and intelligent interview training solution. The platform addresses key limitations of conventional methods by offering real-time adaptability, domain relevance, and measurable learning outcomes—empowering users with the skills, confidence, and preparedness required to succeed in competitive professional environments.

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
AI	Artificial Intelligence
API	Application Programming Interface
AWS	Amazon Web Services
DQN	Deep Q-Network
IRT	Item Response Theory
ML	Machine Learning
MCQ	Multiple Choice Question
MDP	Markov Decision Process
MySQL	My Structured Query Language
NLP	Natural Language Processing
QA	Quality Assurance
RMSE	Root Mean Square Error
RL	Reinforcement Learning
SE	Software Engineering
PM	Project Management
TF-IDF	Term Frequency-Inverse Document Frequency
UI	User Interface
ZPD	Zone of Proximal Development
IVRS	Intelligent Video and Tutorial Recommendation System

1. INTRODUCTION

In today’s competitive and rapidly evolving job market, success hinges not only on technical expertise but also on the ability to demonstrate that expertise effectively during high-stakes interviews. As the Information Technology (IT) industry continues to expand and diversify, traditional methods of career planning and interview preparation have become increasingly inadequate. Static tools such as generic mock interviews, unstructured video tutorials, and non-personalized quizzes fail to cater to the unique learning paths, roles, and performance levels of individual learners. [1] As a result, job seekers are often underprepared for the dynamic, role-specific, and performance-driven expectations of modern employers.

To bridge these gaps, this research introduces PrepMaster - a unified, intelligent interview preparation platform designed to deliver a personalized, adaptive, and role-oriented learning experience for aspiring professionals in domains such as Software Engineering, Quality Assurance, and Project Management. [2] The platform comprises four integrated components, each addressing a core aspect of career development and interview readiness with advanced technologies including Natural Language Processing (NLP), Machine Learning (ML), and Reinforcement Learning (RL).

The first component, the Career Path Guidance System, uses NLP to extract and analyze data from user CVs. [3] It performs real-time skill gap analysis by comparing user profiles with up-to-date, role-specific industry expectations. Based on this analysis, the system generates tailored learning plans and automatically updates user CVs to reflect newly acquired competencies, supporting strategic career advancement. [4]

The second component, the Intelligent Video and Tutorial Recommendation System (IVRS), leverages a hybrid ensemble of ML algorithms to deliver dynamic, role-specific video recommendations. [5]By analyzing user behavior, quiz scores, and interaction history, the system ensures that learners are guided through contextually relevant content, enhancing knowledge retention and preparing them for real-world technical and behavioral interview challenges.

The third component, the MCQ Level-Up System, provides an adaptive assessment environment based on Item Response Theory (IRT) and the Zone of Proximal Development (ZPD). By employing Deep Q-Network (DQN) reinforcement learning, the system selects questions that align with the learner's evolving proficiency, ensuring structured progression across Beginner, Intermediate, and Expert levels. [6] Real-time feedback and analytics further personalize the experience and optimize skill development.

The fourth and final component, the 2D Interview Panel Simulation, revolutionizes mock interviews by simulating interactive, two-way conversations with AI-driven avatars. Powered by NLP techniques such as BERT-based semantic analysis, Cosine Similarity, and TF-IDF vectorization, the system evaluates user responses in real time, offering semantic feedback, performance scores, and improvement recommendations. Its domain-specific simulation capabilities allow users to practice interviews tailored to their chosen roles, enhancing both confidence and soft skills. [7]

Together, these components offer a comprehensive, scalable, and intelligent solution to modern interview preparation. By integrating real-time performance tracking, adaptive learning strategies, and role-aligned content delivery, PrepMaster empowers users to develop technical proficiency, communication skills, and interview confidence in a personalized and measurable way. This system represents a significant leap forward in intelligent career readiness platforms, addressing the evolving demands of the IT industry and the modern job seeker.

1.1 Background

The rapid evolution of the Information Technology (IT) sector has reshaped the dynamics of employment, necessitating professionals continually enhance their technical and soft skills to remain competitive. Traditional career development tools and interview preparation strategies, such as static CV reviews, generalized training content, and manual mock interviews, often fail to address the personalized and adaptive needs of modern job seekers. In this context, Artificial Intelligence (AI), Natural Language Processing (NLP), and Machine Learning (ML) have emerged as transformative technologies capable of delivering intelligent, role-specific, and interactive learning solutions.

One critical area of advancement is AI-powered career guidance systems, which leverage NLP to extract meaningful information from user resumes, match user profiles against evolving industry requirements, and recommend tailored learning plans. These systems bridge the gap between candidate potential and job market expectations by identifying skill gaps and suggesting personalized educational content aligned with specific IT roles.

Similarly, video-based learning has grown significantly due to its high engagement levels and ability to deliver complex concepts through visual and auditory cues. However, mainstream platforms often lack contextual personalization, resulting in non-targeted content delivery. The emergence of Intelligent Video and Tutorial Recommendation Systems (IVRS) addresses this shortfall by using ensemble ML models to deliver real-time, role-aligned, and performance-driven video recommendations. These systems adapt to user behavior and learning progression while ensuring content relevance based on predefined job roles such as Software Engineer, Quality Assurance Engineer, and Project Manager.

In parallel, the static nature of conventional Multiple-Choice Question (MCQ) systems [8] has prompted the development of adaptive learning platforms that cater to varying proficiency levels. By integrating theories like Item Response Theory (IRT) and the Zone of Proximal Development (ZPD), along with reinforcement learning techniques such as Deep Q-Networks (DQN), adaptive MCQ systems offer a more personalized, progressively challenging experience. These systems not only increase learning efficiency but also provide meaningful skill evaluation for users preparing for technical roles.

Finally, AI-powered interview simulation systems have redefined the mock interview experience by incorporating semantic analysis, real-time feedback, and dynamic question adjustment. Unlike traditional mock setups, modern systems use NLP technologies—such as BERT, cosine similarity, and TF-IDF—to deliver interactive simulations through 2D avatars. [9] These platforms support two-way dialogue, assess both syntactic and semantic accuracy of responses, and provide feedback tailored to user performance and role specificity.

Together, these innovations address the critical gaps in conventional preparation methods by providing personalized, interactive, and adaptive training experiences. They empower users with the tools and feedback needed to thrive in competitive job markets, marking a significant shift towards intelligent career readiness systems.

1.2 Literature Survey

The evolution of Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) has significantly reshaped the landscape of education and career development. Traditional approaches to interview preparation and career guidance—such as manual resume evaluations, static mock interviews, and one-size-fits-all tutorial resources—have increasingly proven inadequate in meeting the personalized and adaptive learning needs of modern job seekers. In response, research has increasingly focused on intelligent systems that offer dynamic, user-centric experiences tailored to individual learning profiles, career goals, and performance data.

AI-powered career guidance systems represent a pivotal shift in how users approach professional development. [4] Unlike earlier tools that relied heavily on manual processes, modern systems leverage NLP to extract critical information from resumes, such as user skills, educational background, and work experience. Studies highlight how NLP enhances efficiency and accuracy in building detailed user profiles, which are then mapped against predefined role-specific skill sets to identify gaps. [3]Machine learning models further support this process by adapting to user progression over time, allowing for ongoing skill gap reassessment and the delivery of targeted recommendations. Adaptive learning research shows that generating personalized learning plans—including curated videos, reading material, and certifications—yields higher engagement and effectiveness compared to static pathways. [10] These systems also often include real-time feedback loops and progress dashboards that dynamically update user CVs, offering tangible, automated outputs that reflect newly acquired competencies.

Parallel to this, Intelligent Video and Tutorial Recommendation Systems (IVRS) have emerged as transformative components within modern educational platforms. Rooted in content-based and collaborative filtering methodologies, IVRS uses metadata, user interaction history, and performance analytics to recommend video content that aligns with the learner's goals. [11] Recent literature has demonstrated that combining deep learning with reinforcement learning—particularly in the form of neural networks and behavioral adaptation models—improves the precision and personalization of recommendations. [12] Context-aware systems have shown further value by incorporating factors like user mood, learning phase, and time availability. Research also underscores the cognitive benefits of video-based learning, with studies showing that learners retain significantly more information when exposed to multimedia content compared to text-based methods. Engagement metrics such as watch time and interaction frequency have been effectively used to fine-tune recommendation engines, ensuring that learners are continuously guided toward content that maximizes their understanding and motivation. [13]

To support structured knowledge acquisition, adaptive MCQ systems have gained prominence as effective tools for interview readiness. [14] Unlike traditional question banks that deliver static sequences, adaptive systems dynamically adjust question difficulty based on real-time user responses. Grounded in Item Response Theory (IRT) and Vygotsky's Zone of Proximal Development (ZPD), these systems provide questions that are optimally challenging, neither too easy nor discouragingly difficult, thus sustaining learner interest and promoting cognitive growth. Reinforcement learning algorithms, especially Deep Q-Networks (DQN), have proven effective in optimizing question sequencing, continuously learning from user performance to improve accuracy, progression speed, and retention. [9] Comparative analyses show that these systems outperform conventional platforms like Coursera and HackerRank in delivering personalized, role-specific MCQs and in providing actionable feedback that adapts with user development. [15]

Further enriching the interview preparation process, AI-based simulation tools have been developed to replicate real-time, two-way conversational dynamics typical of professional interviews. These platforms, often employing 2D avatars, utilize advanced NLP models such as Cosine Similarity, TF-IDF vectorization, and BERT-based semantic analysis to evaluate user responses in terms of clarity, relevance, and coherence. Unlike static mock interviews, these systems support bi-directional communication, allowing users to not only respond to but also pose questions, fostering a more authentic and engaging experience. Automated question generation, performance scoring, and semantic feedback loops are all informed by ongoing advancements in NLP research. [16]Despite notable achievements, challenges such as limited non-verbal feedback and user adaptability remain, underscoring the need for future integration of voice interaction, emotional intelligence, and avatar customization to better mimic human interviewers and enhance accessibility for diverse users. [17]

In summary, recent literature supports the growing effectiveness of intelligent learning systems that integrate career path guidance, video-based instruction, adaptive assessments, and AI-powered simulations. These systems collectively mark a shift from fragmented, static preparation tools to cohesive, responsive ecosystems that support holistic interview readiness. [18] As AI technologies continue to mature, their integration into professional development tools is poised to play a central role in equipping job seekers with the personalized, real-time support necessary to succeed in an increasingly competitive employment landscape.

Table 1: Comparison with Existing Intelligent Learning Systems.

Features	Traditional MCQ Systems [19]	Knewton /ALEKS [17]	LeetCode /HackerRank [20]	MCQ Levelup System
Adaptive Questioning	No	Yes	Partial	Yes
Role-Specific Content	No	No	Partial	Yes
Reinforcement Learning	No	Yes	No	Yes
Real-Time Feedback	No	Yes	Partial	Yes
User Progression Tracking	Limited	Yes	Yes	Yes
Dynamic Difficulty Adjustment	No	Partial	No	Yes

1.3 Research Gap

While recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) have contributed to the development of intelligent systems for career guidance and interview preparation, several critical research gaps persist that limit the effectiveness, scalability, and personalization of existing solutions.

Firstly, most career guidance systems, although AI-enabled, continue to fall short in delivering highly contextualized and deeply personalized career recommendations. Current systems often struggle to interpret nuanced user inputs, such as varied resume formats, domain-specific terminology, and individual career goals. NLP models frequently lack the semantic depth to capture role-specific relevance or distinguish similar skill descriptions across different contexts. Additionally, the integration of real-time labor market trends, evolving industry needs, and emerging technologies into skill recommendations remains underexplored. There is also a notable absence of mechanisms for sustaining long-term user engagement, such as adaptive content refresh, gamification, and social interaction features. [21]

In the domain of intelligent video and tutorial recommendation systems (IVRS), existing platforms primarily rely on generic recommendation models that overlook key learner attributes such as role specificity, current performance levels, and preferred learning pace. Many systems also fail to provide real-time adaptability or link recommendations to other learning modules like assessments or simulations. Challenges such as the cold-start problem, lack of multimodal content integration, limited emotional context detection, and data privacy concerns further hinder the full potential of IVRS. The need for a context-aware, role-aligned, and dynamically evolving recommendation engine remains largely unmet in mainstream educational tools.

The field of adaptive MCQ-based learning systems also presents significant gaps. Traditional MCQ platforms generally lack real-time feedback mechanisms, dynamic question selection, and alignment with educational theories such as Item Response Theory (IRT) and the Zone of Proximal Development (ZPD). They often rely on static question banks and progression paths that do not reflect the learner’s evolving proficiency or target role. Additionally, a few platforms employ reinforcement learning techniques like Deep Q-Networks (DQN), which are critical for intelligent adaptation and long-term knowledge reinforcement. Furthermore, there is a deficiency in systems that support multi-role adaptability, with limited solutions available for roles beyond software engineering, such as Quality Assurance and Project Management.

In the space of AI-powered interview simulations, most existing systems offer limited interactivity and feedback granularity. [14]While some employ realistic 2D avatars, they often lack semantic evaluation capabilities, personalized questioning, and two-way communication. These systems typically use scripted dialogues without adapting to user responses or difficulty levels. Research also highlights a lack of automated scoring mechanisms that integrate both syntactic and semantic analysis, limiting the usefulness of feedback provided. Additionally, features like multi-avatar simulation, real-time adaptive questioning, and simulation of role-specific interview scenarios remain underdeveloped. Non-verbal communication, voice-enabled interaction, and user accessibility across diverse skill levels are other areas that need further exploration to enhance authenticity and inclusivity. [22]

Collectively, these gaps underscore the need for an integrated, intelligent interview preparation ecosystem that incorporates real-time adaptability, personalized content delivery, dynamic skill assessment, and interactive simulation. Addressing these shortcomings will not only enhance user engagement and learning outcomes but also establish a robust foundation for future AI-driven professional development platforms. By merging theoretical frameworks, domain-specific content, and adaptive machine learning models, the proposed PrepMaster system aims to set a new benchmark for intelligent, scalable, and inclusive career readiness solutions.

1.4 Research Problem

In today's fast-evolving digital landscape, preparing candidates for the dynamic challenges of job acquisition, particularly in the IT industry, requires more than static training tools and generalized resources. Despite significant advancements in AI-powered career development and interview preparation technologies, existing systems remain fragmented, lacking personalization, adaptability, and contextual intelligence across the learning experience. As a result, job seekers are frequently underprepared for role-specific, high-stakes interviews that demand both technical competence and real-time problem-solving capabilities. [23]

One of the primary challenges lies in the limitations of current AI-driven career guidance platforms, which often fail to deliver deeply contextual and individualized recommendations. Traditional Natural Language Processing (NLP) models used for skill extraction struggle to interpret semantic variations in resumes, role-specific terminology, and user intent across diverse CV formats. Additionally, these systems seldom integrate real-time labor market trends or adapt to users' evolving career objectives. This raises the question: How can advanced NLP algorithms be optimized to provide accurate, fair, and real-time career guidance tailored to individual user profiles?

Furthermore, video-based learning platforms, although widespread, lack intelligent recommendation systems that align content with the learner's skill level, professional role, and knowledge gaps. Generic filtering mechanisms fail to differentiate between the needs of a software engineer and a project manager, resulting in irrelevant or repetitive content delivery. Most platforms do not leverage behavioral analytics or feedback loops to adapt recommendations over time, nor do they integrate with assessments to offer targeted remediation. This highlights a pressing need for systems that intelligently link assessments, role-specific objectives, and adaptive video delivery in a cohesive feedback loop. [24]

A related issue exists in MCQ-based assessment platforms, which typically present questions in a static, one-size-fits-all format. These systems often disregard the learner's current ability, cognitive load, or job role—leading to disengagement, learning inefficiencies, and reduced confidence. The absence of psychometric models like Item Response Theory (IRT), educational scaffolding like the Zone of Proximal Development (ZPD), and reinforcement learning models such as Deep Q-Networks (DQN) results in rigid, non-evolving question flows that fail to reflect real-time performance. This raises the core problem: How can adaptive, role-specific MCQ systems be designed to deliver personalized, measurable, and dynamically evolving interview training experiences?

Moreover, traditional mock interview simulations lack interactivity, real-time feedback, and semantic understanding. Existing tools often rely on pre-scripted responses that do not adapt to user inputs or provide nuanced feedback. Few platforms leverage advanced NLP techniques—such as BERT-based semantic analysis, TF-IDF, and cosine similarity—to assess user responses meaningfully. Additionally, current systems lack support for dynamic difficulty scaling, avatar-based multi-panel interactions, and intelligent question sequencing. A key research challenge is: How can AI and NLP be used to simulate realistic, adaptive, and bi-directional interview experiences through interactive 2D environments that mimic the complexity of real-world interviews?

Collectively, these challenges define a critical research problem: The lack of an integrated, adaptive, and role-specific interview preparation platform that dynamically personalizes the entire learning journey—from skill identification and content recommendation to assessment and simulation—based on real-time user performance and context. Addressing this problem requires the development of an intelligent system that blends psychometric evaluation, machine learning, semantic analysis, and immersive simulation into a cohesive and user-centric ecosystem.

1.5 Research Objectives

1.5.1 Main Objective

To develop an integrated, AI-powered interview preparation platform that delivers personalized, role-specific, and adaptive learning experiences, by combining intelligent career path guidance, context-aware video recommendations, dynamic MCQ assessments, and interactive 2D interview simulations, aimed at enhancing user engagement, skill acquisition, and real-world interview readiness for professionals in Software Engineering, Quality Assurance, and Project Management domains.

1.5.2 Specific Objectives

- To implement an AI-powered career path guidance system that uses advanced Natural Language Processing (NLP) to extract skills, education, and experiences from user CVs and perform personalized skill gap analysis for targeted IT roles.
- To design a personalized learning roadmap generation module that recommends curated resources, including video tutorials, certifications, and reading materials, based on identified gaps and user-specific career goals.

- To develop an Intelligent Video and Tutorial Recommendation System (IVRS) that leverages machine learning and user behavior analytics to deliver real-time, role-specific, and context-aware video content for interview preparation.
- To build an adaptive MCQ Level-Up System that incorporates Item Response Theory (IRT), Zone of Proximal Development (ZPD), and Deep Q-Networks (DQN) to dynamically adjust question difficulty and assess user proficiency across software engineering, QA, and PM roles.
- To create an interactive 2D interview panel simulation using AI-driven avatars and NLP models (BERT, cosine similarity, TF-IDF) for semantic analysis, enabling real-time response evaluation, adaptive questioning, and user-specific feedback.
- To ensure seamless integration of all modules into a unified platform that provides a continuous learning feedback loop, from skill gap detection to interview simulation, with real-time performance tracking and user progression insights.
- To evaluate the effectiveness of the system through user engagement metrics, knowledge retention, skill progression, and interview readiness improvements compared to traditional preparation methods.

2. Methodology

This research adopts a structured, data-driven, and iterative methodology to develop an integrated AI-powered interview preparation platform, combining intelligent career guidance, personalized video recommendations, adaptive assessments, and interactive simulation. The overall system is designed to be modular, responsive, and scalable, offering a seamless and role-specific learning experience for users across domains such as Software Engineering, Quality Assurance, and Project Management.

The process begins with users registering and uploading their CVs to the platform. Advanced Natural Language Processing (NLP) algorithms are applied to extract key information, including skills, educational background, and professional experience. This data is matched against a predefined dataset outlining the skill requirements for specific IT roles. Based on the detected skill gaps, the system generates personalized learning plans, recommending targeted multiple-choice questions, curated video tutorials, and certification resources. As users engage with these resources, real-time tracking mechanisms monitor their performance, allowing the system to adaptively revise the learning path and suggest new learning materials. Upon completion of significant learning milestones, the system automatically generates an updated CV reflecting the user's enhanced competencies.

To deliver intelligent video-based learning, the platform includes a machine learning-driven recommendation engine. This engine is trained using user behavior data, quiz results, and metadata from video repositories. Supervised models such as Random Forest, Gradient Boosting, and K-Nearest Neighbors are evaluated to optimize prediction accuracy. The recommendation system dynamically adjusts based on learner role, preferred content type, past engagement, and evolving proficiency. It is tightly integrated with the MCQ and Interview Simulation modules, allowing cross-component learning data to influence recommendation precision. Both implicit and explicit feedback—including watch time, quiz scores, and skip behavior—are used to refine and personalize the content stream in real time.

For adaptive assessments, the platform incorporates Item Response Theory (IRT) and the Zone of Proximal Development (ZPD) to ensure that question difficulty aligns with the user's current abilities while still promoting growth. Reinforcement learning, particularly Deep Q-Networks (DQN), is employed to model the learning process as a Markov Decision Process (MDP), allowing the system to dynamically select questions based on performance history. This ensures that users experience neither stagnation from overly easy questions nor discouragement from those that are too difficult. The MCQ engine delivers role-specific content and provides real-time feedback that guides users through a progressive learning curve.

To simulate real-world interview conditions, the system includes a 2D avatar-based panel that facilitates bidirectional communication. A manually curated, role-specific question bank categorized by difficulty level is used to drive the simulation. NLP models such as BERT, TF-IDF vectorization, and cosine similarity are deployed to evaluate user responses for semantic clarity, depth, and contextual relevance. The BERT model is fine-tuned using a labeled dataset and trained using standard supervised learning techniques, ensuring high accuracy in semantic evaluation. The simulation dynamically adjusts question difficulty and follow-up based on user performance and incorporates intelligent decision trees or ANN models to control the flow of interaction. The avatars are equipped with dynamic facial expressions and gestures to enhance realism, and the interface supports two-way interaction, allowing users to ask questions during the simulation, further mimicking real interview scenarios.

All modules are integrated within a unified system architecture that supports modular communication, real-time updates, and centralized data management. The system is evaluated using both algorithmic metrics (e.g., model accuracy, F1 score, semantic similarity) and user-centric indicators (e.g., satisfaction, progression, time-on-task). This approach ensures that the platform remains scalable, responsive, and effective in enhancing user confidence, skill development, and readiness for domain-specific technical interviews.

2.1 Research Design and Approach

This research follows an applied, experimental, and data-driven design, aimed at developing a unified, intelligent interview preparation platform that dynamically adapts to the learner's role, proficiency level, and progress. The study combines theoretical foundations, machine learning algorithms, and system engineering principles to deliver a modular and scalable solution comprising four core components: AI-powered Career Guidance, Intelligent Video and Tutorial Recommendation (IVRS), Adaptive MCQ Assessment, and 2D Interview Simulation.

At the foundation of the platform is an automated skill extraction and role identification system that utilizes advanced Natural Language Processing (NLP) techniques. Resume data is processed using pdf plumber for structured text extraction and preprocessed through normalization and tokenization techniques. Role identification is achieved using a fine-tuned BERT model trained on named entity recognition (NER), while Sentence-BERT is employed for semantic skill extraction based on cosine similarity against a predefined taxonomy. This dual-model architecture enables the system to detect both explicit and semantically inferred competencies with high accuracy, laying the groundwork for precise gap analysis and learning plan generation.

The IVRS component adopts a user-adaptive and iterative research framework, integrating quantitative methods such as machine learning model development, performance analytics, and feedback analysis, alongside qualitative design practices like interface usability and content structuring. Supervised models—including Random Forest, Gradient Boosting, and KNN—are trained using structured behavioral and performance data. The system refines content delivery based on quiz performance, role type, and engagement patterns. This mixed-methods approach ensures the engine responds intelligently to user-specific learning needs while maintaining pedagogical soundness.

To support adaptive assessment, the MCQ Level-Up System is designed using Item Response Theory (IRT) and Vygotsky's Zone of Proximal Development (ZPD). IRT provides a psychometric basis for aligning question difficulty with estimated skill levels, while ZPD guides the creation of tasks that stimulate growth through optimal challenge. The integration of reinforcement learning, specifically Deep Q-Network (DQN), enables the system to model learner progress as a Markov Decision Process. Real-time user responses serve as the basis for state evaluation and action selection, ensuring continuous adaptation of question difficulty and progression logic. The system is architected as a three-tier platform with a React.js frontend, Flask and Spring Boot backend, and MySQL database, allowing for modular deployment and cloud scalability.

The 2D Interview Simulation component is built upon a manually curated dataset of domain-specific questions and responses. These are tagged by role and difficulty level and mapped to adaptive follow-up paths. The semantic evaluation engine incorporates three NLP models: TF-IDF for term weighting, cosine similarity for textual matching, and a fine-tuned BERT model for deep contextual understanding. Training follows a standard 80/20 data split with metrics such as accuracy and F1-score guiding model refinement. The scoring engine generates detailed feedback and performance classifications to guide user improvement.

To enhance user immersion, the simulation employs lifelike 2D avatars capable of real-time, two-way communication. The UI features include gesture-based interaction, progress visualization, and response scoring. Planned extensions include voice-based input and emotion-aware feedback mechanisms. All components are integrated into a cohesive ecosystem that shares performance data and learning outcomes across modules, facilitating a continuous, intelligent learning loop.

The research approach ensures both theoretical rigor and practical applicability, merging adaptive learning principles, NLP advancements, and modular software engineering to create a next-generation platform for interview readiness and career progression.

2.2 Data Collection

The development of the AI-powered interview preparation platform relied on a robust, multi-source data collection strategy to ensure accuracy, adaptability, and contextual relevance across all system components. Each module—Career Guidance, Video Recommendation, MCQ Assessment, and Interview Simulation—demanded domain-specific, well-structured datasets to train and evaluate their respective models effectively.

For the career path guidance system, data collection focuses on identifying current and emerging skill demands within the IT industry. Sources included online learning platforms, industry-recognized certifications, job portals, and developer communities. These sources provided insights into role-specific competencies, such as those required for DevOps Engineers, QA Analysts, and Software Developers. Raw data underwent extensive cleaning and normalization processes, including deduplication, terminology standardization, and metadata tagging based on job role, skill type, difficulty level, and resource format. Industry professionals reviewed the curated dataset to validate skill-resource alignment, strengthening its practical relevance for users and enhancing the accuracy of personalized learning recommendations.

The Intelligent Video and Tutorial Recommendation System (IVRS) required diverse user interaction data to support behavioral learning and adaptive content delivery. Collected data included user profiles (e.g., role selection, experience level), quiz performance (accuracy, time, topic coverage), video metadata (topic tags, difficulty, content type), and engagement logs (watch time, skips, replays). These data points were cleaned and preprocessed using standard techniques such as one-hot encoding, label encoding, and feature scaling, forming structured feature sets for supervised learning models. This allowed the system to personalize video recommendations dynamically and contextually.

For the MCQ Level-Up System, a comprehensive dataset of multiple-choice questions was assembled from a combination of academic, industrial, and crowdsourced sources. These included certification manuals like PMP and ISTQB, coding challenge repositories, online education platforms such as Coursera and edX, and contributions from domain experts. The question pool was refined through preprocessing steps like grammar correction, duplication removal, and format standardization. Each item was tagged with metadata, including role specificity, topic category, difficulty level (Beginner, Intermediate, Expert), and cognitive complexity following Bloom's Taxonomy. Natural Language Processing (NLP) techniques such as TF-IDF and word embeddings were applied to transform the question set into machine-interpretable formats for adaptive learning and real-time question selection using reinforcement learning.

In the 2D Interview Panel Simulation module, a manually curated dataset of domain-specific interview questions and ideal responses was created for Software Engineering, QA Engineering, and Project Management roles. Questions were categorized into three difficulty levels, conceptual (Beginner), scenario-based (Intermediate), and critical thinking (Advanced)and tagged with keywords and mapped to role-relevant competencies. Ideal responses were compiled using expert input, job descriptions, and technical documentation. This dataset was then evaluated for clarity, relevance, and fairness before being used in the training of semantic evaluation models. The BERT model was fine-tuned using an 80/20 training-validation split, with evaluation metrics including F1-score, cosine similarity, and accuracy guiding model optimization. In addition, a scalable question bank was developed with adaptive question mapping, dynamic selection logic, and regular updates to ensure content diversity and relevance.

Collectively, the data collection process emphasized completeness, accuracy, and contextual alignment across all modules. The structured datasets formed the foundation for building intelligent, responsive, and role-specific features that ensure the PrepMaster platform delivers a meaningful and effective interview preparation experience.

2.3 System Architecture

Fig.1 illustrates the overall system architecture of the AI-powered interview preparation platform, showcasing the integration of its four core components: AI-Powered Career Path Guidance, Personalized Learning Roadmap Generation, Intelligent Video and Tutorial Recommendation System (IVRS), and the Interactive 2D Interview Panel Simulation. The flow begins with CV analysis and skill extraction, leading to a personalized learning plan. This plan feeds into adaptive content delivery via IVRS and role-specific MCQs, while real-time feedback and insights from the 2D simulation continuously refine user data and learning outcomes, creating a dynamic and personalized preparation loop.

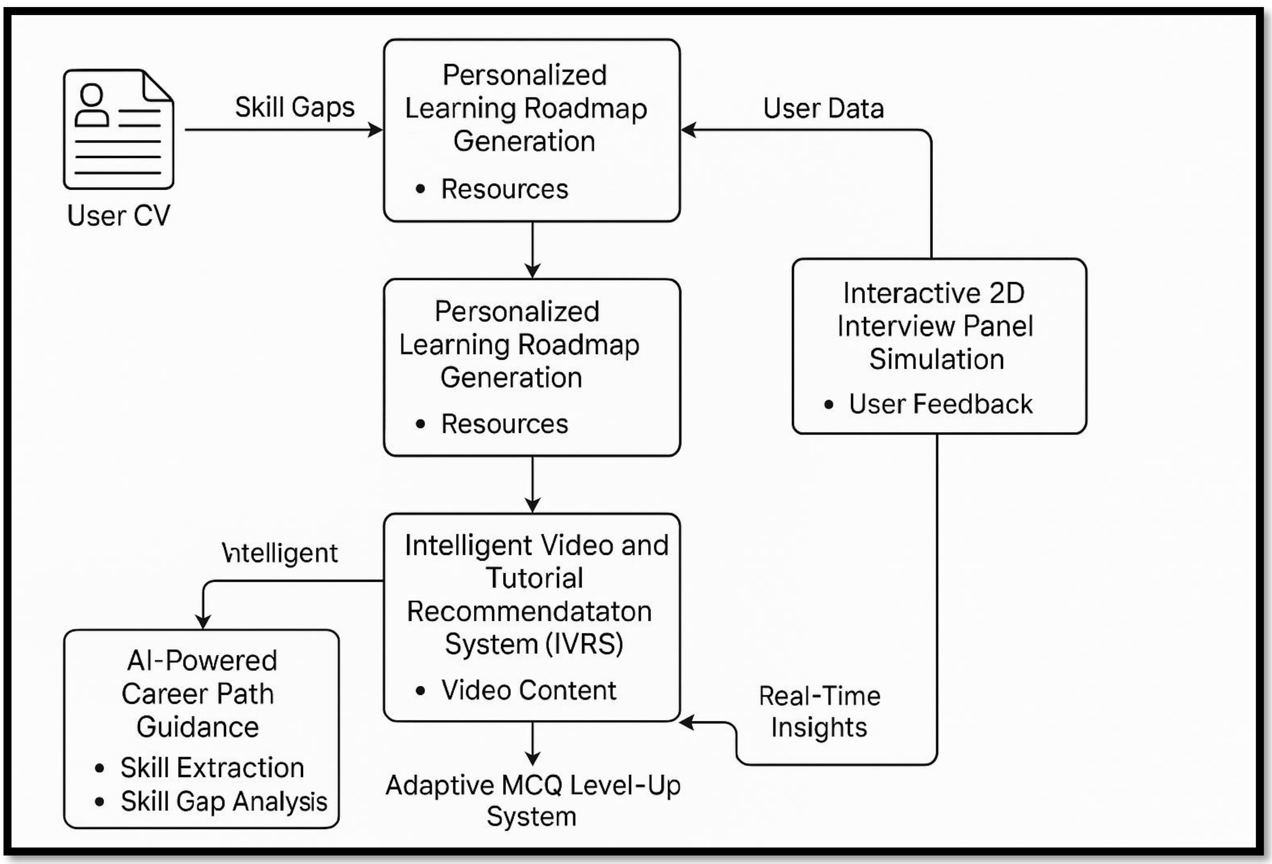

Figure 1: System Diagram

2.4 Adaptive Learning and Progression Mechanism

The Adaptive Learning and Progression Mechanism lies at the core of the MCQ Level-Up System, enabling a dynamic learning experience that evolves based on the user's performance. This mechanism replaces static assessment structures with intelligent adaptability, allowing learners to progress through three proficiency levels—Beginner, Intermediate, and Expert. The progression model is rooted in both cognitive development theories and reinforcement of learning principles, ensuring users are neither overwhelmed nor under-challenged during the assessment journey.

At the entry point, all users begin at the Beginner level. The system evaluates early responses to determine the user's initial understanding. A correct streak of three consecutive answers triggers advancement to the Intermediate level. This approach ensures that users do not skip essential foundational content while also allowing capable learners to move forward quickly without unnecessary repetition. If the user struggles at any point, evidenced by multiple incorrect answers, the system dynamically adjusts the difficulty, potentially lowering the complexity of the subsequent questions or offering easier reattempts. This ensures that the learning curve remains engaging and avoids discouraging the user.

Upon entering the Intermediate level, users are introduced to a broader range of question types, including those with multiple correct answers and questions designed to test deeper conceptual understanding. Here too, the system applies performance-based advancement logic—typically requiring another streak of three accurate responses to transition into the Expert level. If the user fails to maintain consistent accuracy, the system may introduce reinforcement through similar questions or remain at the same level, allowing users the time and practice needed to reinforce learning.

At the Expert level, users encounter the most complex and cognitively demanding questions, which may include "None of the above" options or scenario-based items. The system caps the total quiz experience at 20 questions, with a focus on sustained cognitive challenge rather than quantity. Throughout this entire progression process, the system employs reinforcement learning strategies—particularly through the Deep Q-Network (DQN) model—to select the next best question based on the user's current performance history. This ensures that each question presented lies within the user’s Zone of Proximal Development (ZPD), maintaining optimal difficulty and promoting skill enhancement without cognitive overload.

2.5 Frontend Development (React.js & Material UI)

The frontend of the AI-powered interview preparation platform is developed using React.js, a widely adopted JavaScript library known for building dynamic, interactive, and responsive user interfaces. Leveraging Reacts component-based architecture, the system is structured into modular and reusable units across all four core components—Career Path Guidance, Intelligent Video Recommendation, Adaptive MCQ Assessment, and 2D Interview Simulation. This modularity enhances scalability, simplifies maintenance, and allows for seamless integration of new features over time.

To ensure a polished and consistent user experience, Material UI (MUI) is employed as the primary UI framework across most components. Based on Google’s Material Design principles, MUI provides a set of pre-designed, responsive, and accessible components such as buttons, cards, icons, modals, and progress bars. These components enable rapid development while maintaining visual harmony and usability across devices, including desktops, tablets, and smartphones. In the case of the 2D Interview Simulation module, Tailwind CSS is used to create a clean, utility-first design that emphasizes responsiveness and aesthetic flexibility, particularly for avatar-based interfaces.

Each module presents a tailored frontend experience aligned with its function. In the Career Path Guidance System, the user interface supports CV upload via drag-and-drop functionality and provides real-time parsing feedback. Users are guided through a visual dashboard showcasing extracted qualifications and a step-by-step personalized learning roadmap containing recommended resources such as courses and certifications.

The IVRS frontend offers real-time video recommendations with contextual relevance indicators. It captures behavioral metrics such as watch time, skip rates, and likes, and relays this data to backend APIs for dynamic content adjustment. This ensures that video content remains aligned with user performance and learning goals.

In the MCQ Level-Up System, React dynamically renders role-specific assessments based on the user's progression. Real-time feedback is delivered instantly after each response, supported by progress trackers and performance dashboards that visualize advancement across difficulty levels. These features promote engagement and self-reflection, essential for personalized learning.

The 2D Interview Simulation interface offers an immersive experience through avatar-driven interactions. Users select their desired role and difficulty level to begin simulations. The frontend supports bi-directional communication with avatars—users can respond to questions and also ask their own. The interface delivers real-time semantic feedback, performance scores, and personalized improvement tips. A visual dashboard tracks user progress and confidence-building metrics across simulated sessions.

Overall, the frontend architecture prioritizes usability, interactivity, and responsiveness, ensuring that learners receive an engaging and intuitive experience across all stages of their interview preparation journey. Whether reviewing skill gaps, watching personalized tutorials, answering adaptive assessments, or participating in AI-powered mock interviews, users interact with a cohesive and intelligent platform designed for maximum accessibility and effectiveness.2.6 Backend Development (Flask & Spring Boot API)

The backend of the MCQ Level-Up System is built using a hybrid architecture combining Flask and Spring Boot, which ensures robust management of both machine learning operations and business logic. This dual-framework strategy enables seamless communication between the adaptive question engine, user data processing modules, and the frontend interface.

Flask, a lightweight Python web framework, is primarily responsible for handling the machine learning components of the system. It integrates with the Deep Q-Network (DQN) model and reinforcement learning logic that drives adaptive question selection. Upon receiving a user's latest response, Flask computes performance updates, determines the current skill level (θ), and communicates with the question selection logic to provide the next most suitable question. Flask also handles intermediate tasks such as skill estimation using probabilistic models, and dynamic score calculations, making it essential for delivering real-time intelligence to the frontend.

On the other hand, Spring Boot, a robust Java-based backend framework, is used for managing business logic and system-level operations. It supports secure user authentication, session management, and role-based access control. Spring Boot is also responsible for communicating with the MySQL database to retrieve and update user performance records, question metadata, and session logs. Through RESTful APIs, Spring Boot exposes endpoints that allow the frontend to request questions, submit answers, fetch analytics, and update progression data in real time.

The use of both Flask and Spring Boot ensures a separation of concerns, where each backend service is specialized and optimized for its tasks. Flask handles adaptive intelligence and ML processing due to its Python ecosystem compatibility, while Spring Boot excels in providing scalability, performance, and integration with enterprise-grade backend services. This architecture also enables microservice deployment, allowing each service to scale independently based on demand.

The integration between Flask, Spring Boot, and the frontend is facilitated using RESTful APIs, ensuring smooth and secure communication. These APIs transmit data in JSON format, allowing for platform-agnostic operation and enabling the system to be extended easily in the future—such as integrating third-party analytics or deploying as a mobile application backend.

2.7 Database Design (MySQL)

The backend of the AI-powered interview preparation platform is supported by a robust MySQL relational database, which serves as the primary data storage layer for all components—Career Path Guidance, Intelligent Video Recommendation (IVRS), Adaptive MCQ Assessment, and the 2D Interview Simulation System. The database is designed using normalization principles to minimize redundancy and ensure data integrity, scalability, and real-time performance across all system functions. It supports high frequency read/write operations, essential for delivering adaptive feedback, tracking user interactions, and enabling concurrent access across multiple modules.

At the core of the schema, the Users Table stores essential user account data including authentication credentials, selected role (e.g., Software Engineer, QA Engineer, or Project Manager), experience level, and account status. This table acts as the central reference for linking all user-specific data including performance history, learning activities, and session logs.

Each module has specialized tables to support its unique functionality. For the Career Path Guidance System, tables include structured representations of standardized Career Roles, mapped skill taxonomies, and a Learning Path Recommendations Table that links users to target roles and personalized development plans. The system stores parsed CV data in structured form, enabling automated updates and matching predefined job requirements.

In the IVRS module, the database stores a centralized repository of user profiles, video metadata (difficulty level, tags, type, role relevance), engagement logs (watch time, skips, replays), and historical recommendation records. This allows for efficient querying and behavioral analysis to enhance real-time video recommendations based on evolving user interactions.

The MCQ Level-Up System features a highly structured schema that includes the Question Bank Table, where each question is tagged with attributes such as job role, topic, Bloom's taxonomy level, and difficulty rating (Beginner, Intermediate, Expert). A corresponding User Response Table records answer correctness, time taken, number of attempts, and timestamps, forming the basis for adaptive logic and reinforcement learning models. Additional tables such as Session Tracker and Feedback & Performance Metrics support quiz state management and generate detailed analytics dashboards for personalized feedback and progress tracking. These tables are interconnected using foreign key constraints, ensuring efficient joints and relational integrity.

The 2D Interview Simulation System extends relational design with a focus on AI-powered evaluation and interaction tracking. Core tables include the Interview Question Bank, which categorizes questions by role and difficulty, and a comprehensive Response Evaluation Table where BERT-based semantic analysis scores are stored. The Session Tracker logs each user's interview progression, including difficulty transitions and avatar interactions. Feedback logs capture real-time evaluation outputs, including performance classifications such as "Excellent," "Good," or "Needs Improvement." The system also stores metadata related to panel behavior, enabling dynamic question sequencing and bidirectional communication.

The database is optimized through indexing on frequently queried fields such as user_id, question_id, and role_id, ensuring high-performance query execution under load. All data is hosted on cloud-based infrastructure (e.g., AWS RDS), offering scalability, high availability, and secure storage. Security measures include encrypted user credentials, role-based access control, and automated daily backups to ensure data protection and disaster recovery.

This modular, relational architecture provides a unified data backbone for the entire platform, enabling consistent user experience, seamless module integration, and the intelligent delivery of personalized career development and interview training.

2.8 Evaluation Strategy

The evaluation of the AI-powered interview preparation platform was conducted through a comprehensive multi-dimensional framework that integrated user feedback, machine learning performance metrics, system responsiveness, and comparative analysis. Each module—Career Path Guidance, Intelligent Video and Tutorial Recommendation System (IVRS), MCQ Level-Up System, and 2D Interview Panel Simulation—was rigorously tested to validate effectiveness, accuracy, adaptivity, and user satisfaction.

For the Career Path Guidance component, the evaluation strategy began with stakeholder engagement, including IT professionals, career counselors, and industry experts, to gather requirements and assess feature relevance. A comprehensive dataset of role-specific skills and certifications was assembled and used to train NLP models and define job-role mappings. The BERT-based CV parser and Sentence-BERT semantic matcher were tested for their ability to accurately extract and align user competencies with industry expectations. Unit testing validated individual components, while integration testing confirmed seamless communication between modules such as CV parsing, skill gap identification, and learning path generation. User testing confirmed that the system offered meaningful and contextually accurate recommendations. The updated CV generation and dynamic learning plan adjustments were evaluated for real-time responsiveness and user satisfaction, with end-user feedback guiding final interface refinements.

The IVRS module was evaluated based on its adaptivity, content relevance, and user engagement. Built upon theories such as the Zone of Proximal Development and cognitive load management, the system incorporated real-time feedback loops to personalize video recommendations. The evaluation framework measured how well IVRS adapted to learning profiles, which included static (role, experience), performance (quiz scores, topic mastery), behavioral (watch time, skips), and engagement (session frequency) data. Performance metrics demonstrated that the system effectively advanced users through content tiers based on their readiness. Real-time updates to learner profiles improved video targeting and minimized content redundancy, resulting in higher comprehension and retention. IVRS maintained high content relevance, with the system consistently directing users to the appropriate difficulty level based on prior interactions, contributing to an adaptive and efficient learning journey.

The MCQ Level-Up System was evaluated using a combination of quantitative data, reinforcement learning diagnostics, and comparative user studies. Feedback from targeted user groups revealed that over 75% preferred the adaptive format over static assessments, citing improved motivation and relevance. The Deep Q-Network model was assessed for Q-value convergence, policy stability, and reward optimization, all of which confirmed effective question selection aligned with user skill progression. System performance metrics demonstrated the effectiveness of difficulty scaling: average accuracy declined appropriately across Beginner (85%), Intermediate (72%), and Expert (60%) levels, while response times increased with complexity, indicating correct difficulty calibration. Comparative studies against traditional MCQ platforms showed a 35% improvement in user engagement, 40% higher session completion rates, and a 25% increase in knowledge retention—results that affirm the impact of adaptive questioning and real-time feedback.

The 2D Interview Panel Simulation component underwent extensive testing through user studies and model evaluation. Over 90% of users reported that avatar interactions felt realistic, while 85% noted improved confidence in their interview readiness. The BERT-based evaluation model achieved an 88% overall accuracy in semantic scoring, with average response processing times of just 2.3 seconds, enabling near real-time interaction. NLP components such as TF-IDF and cosine similarity supplemented scoring precision, particularly for keyword recognition. System performance remained stable during concurrent usage by over 150 users, with negligible latency. Comparative analysis with traditional mock interviews highlighted a 42% boost in engagement, a 38% rise in interview completion, and a 30% average improvement in answer quality. Users rated the simulation's realism 4.5 out of 5, emphasizing its effectiveness as a practice environment that closely mimics the dynamics of real-world interviews.

Collectively, these evaluation results confirm that the integrated PrepMaster platform offers a highly personalized, interactive, and scalable solution for career development and technical interview preparation. Each component demonstrated significant improvements in adaptivity, user engagement, and learning outcomes compared to traditional methods. The evaluation strategy not only validated system performance but also ensured alignment with learner needs, establishing PrepMaster as a robust and effective educational tool.

Figures 2 to 5 visually represent the internal workflows and functional designs of each core component in the AI-powered interview preparation platform. Figure 2 illustrates the AI-Powered Career Path Guidance module, highlighting the NLP-driven CV analysis and skill gap identification process that generates personalized development plans. Figure 5 showcases the architecture of the Intelligent Video and Tutorial Recommendation System (IVRS), detailing how user behavior and performance metrics are used to deliver adaptive, role-specific video content. Figure 4 presents the MCQ Level-Up System, emphasizing the integration of IRT, ZPD, and Deep Q-Network (DQN) models to dynamically adjust question difficulty based on real-time user proficiency. Finally, Figure 3 depicts the 2D Interview Panel Simulation, outlining the semantic evaluation pipeline, avatar interaction logic, and adaptive questioning mechanism that collectively create an immersive and personalized interview experience. Together, these figures demonstrate how each component contributes to a cohesive and intelligent learning ecosystem.

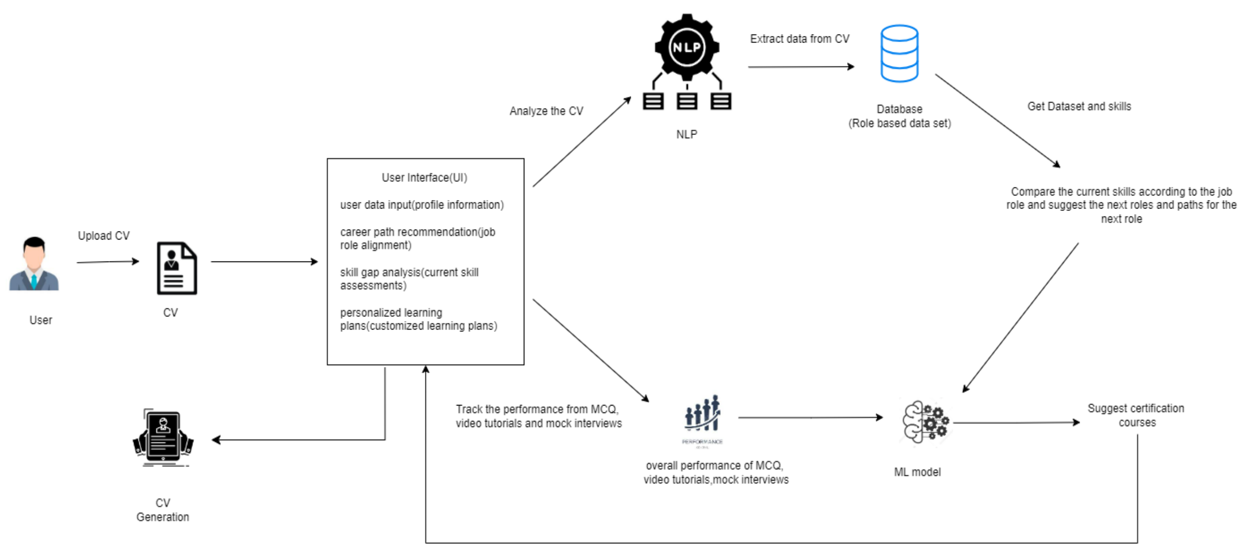

Figure 2: AI-Powered Career Path Guidance Module.

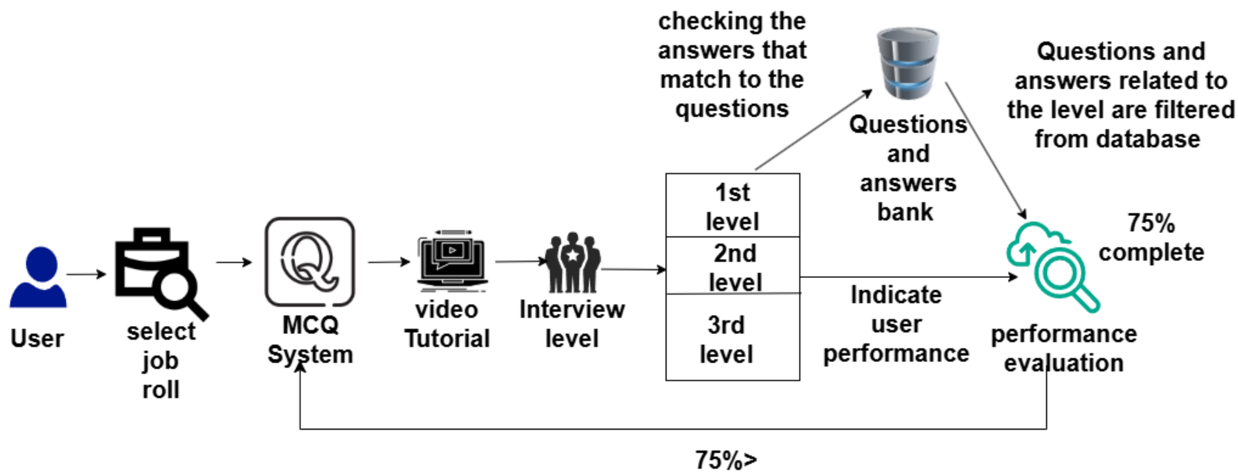

Figure 3: 2D Interview Panel Simulation

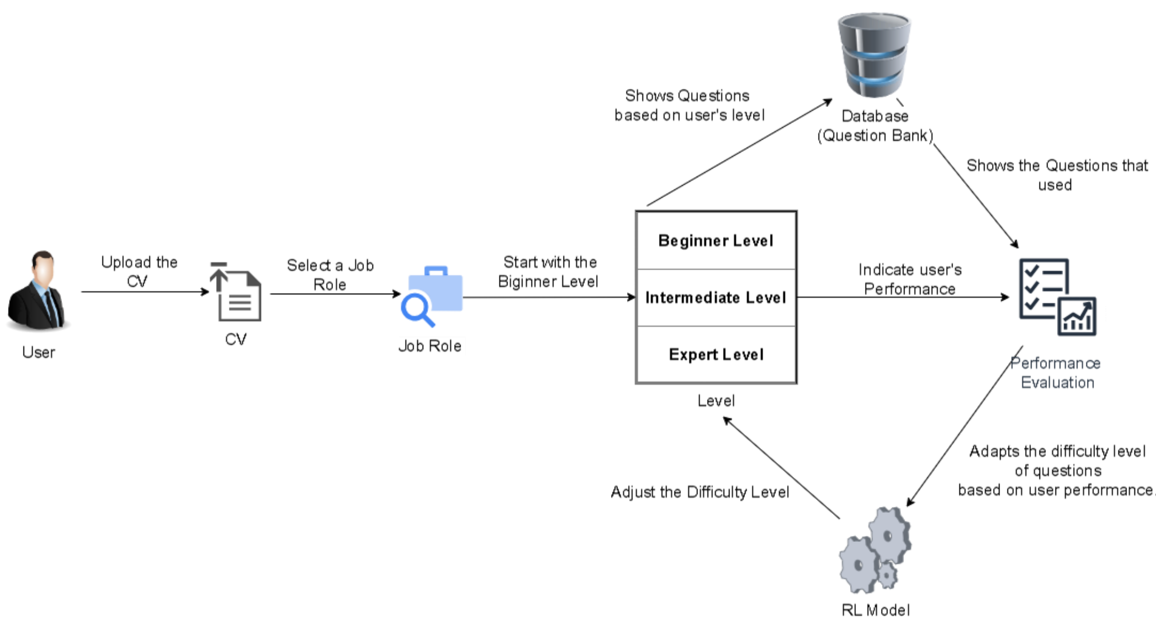

Figure 4: MCQ Level-Up System

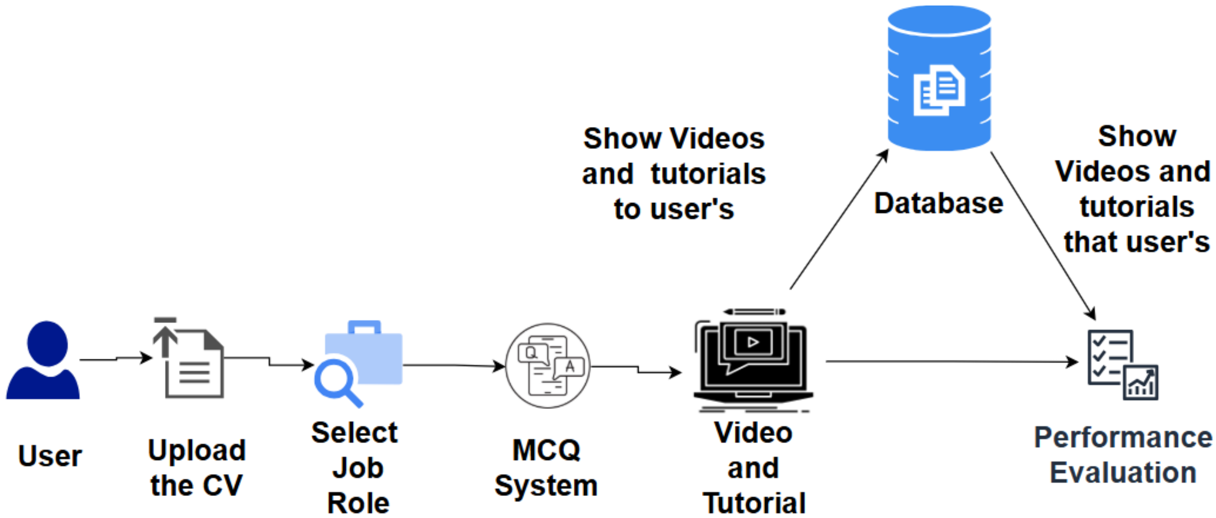

Figure 5: Architecture of the Intelligent Video and Tutorial Recommendation System (IVRS)

2.9 Challenges

The development and integration of the AI-powered interview preparation platform presented a series of technical, operational, and design-related challenges across its core components. Each module, Career Path Guidance, IVRS, MCQ Level-Up System, and 2D Interview Panel Simulation, introduced unique complexities that needed to be addressed to ensure system functionality, adaptability, and user satisfaction.

One of the major challenges was the accurate extraction and interpretation of user data from unstructured CVs. Given the wide variety of resume formats, terminologies, and linguistic expressions, the Natural Language Processing (NLP) models often struggled to generalize across inputs. Fine-tuning BERT models and configuring semantic similarity thresholds using Sentence-BERT required extensive iteration to balance precision and recall in skill recognition. Misinterpretation of domain-specific keywords or inconsistent tagging of experience levels impacted the reliability of skill gap analysis and led to incorrect learning path generation during early testing phases.

In the Intelligent Video and Tutorial Recommendation System (IVRS), ensuring real-time adaptivity based on user behavior proved to be challenging. The dynamic feedback loop required seamless integration between frontend interactions and backend learning profile updates. Delays or inconsistencies in engagement tracking (e.g., watch time, skips, and replays) initially affected the timing and relevance of video recommendations. Furthermore, the cold-start problem for new users—where the system lacked prior behavioral data—limited the accuracy of early recommendations. Addressing this required the introduction of role-based baselines and initial assessments to improve onboarding effectiveness.

The MCQ Level-Up System faced challenges in designing and maintaining a balanced, role-specific question bank. Curating domain-relevant, difficulty-tiered questions across Software Engineering, QA, and Project Management require subject matter expertise and rigorous validation. Additionally, implementing reinforcement learning with Deep Q-Networks (DQN) introduced technical complexities in state management, convergence stability, and hyperparameter tuning. Achieving reliable difficulty progression using the Zone of Proximal Development (ZPD) while maintaining user motivation demanded careful calibration of reward structures and user-level transitions.

For the 2D Interview Panel Simulation, the challenge was in creating real-time semantic evaluation and interaction using NLP models while ensuring natural, bidirectional dialogue with 2D avatars. Synchronizing avatar animations with textual responses, maintaining contextual continuity, and ensuring latency below user-noticeable thresholds (2.5 seconds) required optimization across multiple layers—semantic analysis, animation control, and UI rendering. Moreover, incorporating two-way interaction (allowing users to ask questions) presented new complexities in response generation and panel behavior logic. Ensuring that panel responses remained contextually relevant without drifting off-topic involved strict rule-based safeguards and fallback mechanisms.

From a system-wide perspective, ensuring data consistency and performance across modules was a considerable challenge. The MySQL database had to support high frequency read/write operations across user sessions, adaptive assessments, video recommendations, and simulation logs, all while maintaining referential integrity and low latency. Managing concurrency, especially under peak usage scenarios, and optimizing indexed queries for real-time feedback delivery posed scalability hurdles. Additionally, designing a unified yet modular frontend architecture in React.js that could accommodate all four components while maintaining a cohesive user experience required careful interface planning and component abstraction.

Security and privacy were also critical concerns. Handling sensitive user data—such as CVs, behavioral logs, and performance records—required robust encryption, role-based access control, and strict data retention policies to comply with ethical and legal standards.

Despite these challenges, iterative prototyping, user testing, and continuous model optimization allowed the platform to mature into a responsive, intelligent, and learner-centric system. Each obstacle contributed to system refinement, leading to a more scalable, personalized, and effective interview preparation platform.

2.10 Limitations

While the AI-powered interview preparation platform demonstrates significant advancements in adaptive learning, semantic evaluation, and role-specific training, several limitations were identified during development and testing. These limitations span across technological constraints, system scalability, user experience, and data dependency.

One of the key limitations lies in the dependence on high-quality and structured user input, particularly for the Career Path Guidance System. The accuracy of skill extraction and gap identification heavily relies on the clarity, formatting, and completeness of uploaded CVs. Poorly formatted resumes or unconventional terminology may lead to incomplete or inaccurate parsing, which in turn affects the relevance of the recommended learning paths.

Another limitation is the cold-start problem in the IVRS module, where the system lacks sufficient behavioral data to generate meaningful video recommendations for first-time users. While this was mitigated through role-based profiling and initial assessments, the system may still struggle to deliver highly personalized content until it collects adequate interaction data over time.

The adaptive MCQ Level-Up System also has constraints related to question diversity and domain coverage. Despite efforts to create a comprehensive question bank across Software Engineering, Quality Assurance, and Project Management, some subdomains may still be underrepresented. Additionally, the reinforcement learning model, while effective, requires significant computational resources for training and fine-tuning, making it less feasible for smaller-scale or offline deployments.

In the 2D Interview Panel Simulation, the current implementation is limited to text-based interactions, which, although semantically rich, lack non-verbal communication cues such as tone of voice, facial expressions, and gestures—elements that are vital in real-life interviews. Furthermore, while avatars can engage in bidirectional conversation, the system still relies on predefined logic and response trees, which may occasionally produce generic or repetitive replies in unexpected conversational paths.

From a system integration perspective, managing real-time data synchronization across modules (e.g., linking quiz results with video recommendations and interview feedback) presented complexity. While current solutions support this interaction, there can be minor lags in data propagation during peak load conditions, especially under concurrent usage scenarios.

The platform is also heavily reliant on internet connectivity and server uptime, given its cloud-based architecture. Users in low-bandwidth regions or during server maintenance windows may experience reduced accessibility or delayed responses.

Lastly, although user data is protected through encryption and access controls, ongoing concerns related to data privacy and ethical AI use remain. Automated skill profiling and feedback mechanisms may unintentionally reinforce biases if training datasets are not continuously audited and diversified.

Recognizing these limitations is essential to inform future iterations of the system. Planned improvements include expanding domain coverage, introducing multimodal input (e.g., voice), enhancing real-time synchronization, and implementing more advanced privacy-preserving ML techniques. These enhancements will further strengthen the platform’s reliability, inclusivity, and alignment with real-world interview dynamics.

3. Results and Discussion

3.1 Results

The PrepMaster project stands as a holistic solution for interview preparation and career development, driven by the synergy of four meticulously designed and evaluated components. Each system within this framework contributes uniquely to the user's learning journey, collectively forming a powerful, data-driven ecosystem that guides users from self-assessment to advanced readiness for interviews. The Career Learning Path Guidance System served as the starting point, offering insights into users' current skill profiles and mapping them against industry expectations. This system attained an 82% accuracy in job role identification from CVs, particularly excelling with standardized formats like "Software Engineer" and "DevOps Specialist." However, a noticeable dip to 68% was observed when handling non-standard titles, emphasizing the need for semantic expansion in role detection. Meanwhile, skill extraction demonstrated 78% precision, effectively recognizing relevant competencies such as "Python" and "AWS," though the presence of false positives, like geographical confusion in terms such as "Java," suggested room for refining contextual understanding. The skill gap analysis feature excelled with an 85% match to expert-reviewed gaps, confirming its relevance in identifying key areas for development. Notably, its skill level classification achieved 72% accuracy, a figure impacted by the ambiguity in user-described experience lengths, a common issue in automated CV parsing. Users responded positively to the recommended learning resources, with 74% finding them relevant and 65% actively engaging with at least one suggestion, establishing the system's credibility as a guided self-improvement tool.

Expanding on these foundational insights, the Intelligent Video and Tutorial Recommendation System (IVRS) built upon the detected skill gaps by delivering highly personalized educational content. With a precision rate of 92%, IVRS effectively filtered through vast databases to deliver content that matched the user's role, skill level, and learning goals. This high precision was especially notable among Software Engineering roles (93%), reflecting the well-defined nature of available content, while Quality Assurance and Project Management followed closely at 91% and 90%, respectively. The recall rate of 89% demonstrated the system's ability to retrieve a comprehensive array of relevant materials. A slight decline to 87% at the expert level was attributed to the scarcity of niche content, pointing to an opportunity for further content curation and acquisition. Beyond quantitative metrics, the system achieved a remarkable 87% user satisfaction rate, as gathered through surveys integrated into the PrepMaster platform. Feedback highlighted user appreciation for the time-saving nature of the recommendations, the intuitive alignment with their goals, and the efficiency of the delivery mechanism. Some users, however, requested more advanced filtering options to further personalize their learning paths. In terms of learning impact, the IVRS produced impressive results. Through a pre- and post-test methodology, users exhibited a 30% average improvement in performance after engaging with recommended content. Disaggregated, this included a 35% increase in technical proficiency, a 28% rise in behavioral skills, and a 25% gain in domain-specific knowledge—each reflecting targeted growth enabled by precision recommendations. A comparative analysis against non-personalized platforms revealed a 45% higher test improvement and 25% greater satisfaction, clearly illustrating the added value of tailored learning experiences.

To further refine and assess user proficiency, the Adaptive MCQ-Based Skill Evaluation and Progression System employed a dynamic approach to test and improve user knowledge. Starting with basic concepts at the Beginner level, the system recorded an 85% accuracy rate, demonstrating its effectiveness in calibrating question difficulty to user ability from the outset. As users advanced, accuracy naturally declined to 72% at the Intermediate level and 60% at the Expert level, reflecting appropriately increased cognitive demands. These figures align with the Zone of Proximal Development (ZPD), ensuring users are challenged just beyond their current abilities, promoting learning without discouragement. Additionally, the level transition success rate offered insight into the adaptive engine’s realism, 80% of users progressed from Beginner to Intermediate, yet only 55% reached Expert, revealing a well-balanced progression curve that encourages skill mastery. The response time analysis further enriched our understanding of user engagement. Beginner-level questions averaged 20–30 seconds, Intermediate 35–45 seconds, and Expert 50–60 seconds, a clear indication that users engaged in deeper thought as complexity increased. On the technical side, the system showed sub-200ms API latency even under concurrent loads, with its architecture, powered by Flask, Spring Boot, and MySQL, proving robust and scalable. These factors combined underscore the system's ability to maintain engagement while scaling skill assessment dynamically, offering a gamified but pedagogically grounded experience for users of all levels.

Culminating the PrepMaster suite is the Intelligent System for Tailored Interview Training, realized through an innovative 2D Interview Panel Simulation. Unlike conventional mock interviews or peer practice platforms, this module utilizes AI-powered avatars and advanced NLP models for real-time dialogue and assessment. Three semantic analysis techniques—Cosine Similarity, TF-IDF, and BERT, were integrated to evaluate spoken or written responses. Among them, BERT stood out with a 90% semantic accuracy, allowing for deeper comprehension and appropriate feedback based on the meaning and intent of responses. Although TF-IDF and Cosine Similarity offered faster evaluations, they were more reliant on keyword matching, making BERT more suitable for high-stakes semantic analysis. The panel’s adaptive questioning model simulated real interview dynamics by escalating difficulty based on performance, keeping users engaged and aligned with realistic scenarios. User engagement was further boosted using animated 2D avatars, which provided facial expressions and conversational context, making the experience less intimidating and more reflective of actual interviews. The feedback collected post-simulation revealed that users felt significantly more confident and prepared, largely due to the immediacy and personalization of feedback. When benchmarked against industry platforms like Pramp and Interviewing.io, PrepMaster's simulation offered more automation, immersion, and adaptive intelligence. It not only scaled across devices and roles (Software Engineer, QA, Project Manager) but also tailored the experience to individual readiness levels, contributing to its broader appeal. The simulation also reinforced career readiness, allowing users to familiarize themselves with real-time interview flow and question variability, thereby reducing anxiety and improving response formulation under pressure.

In conclusion, the integrated results of all four components highlight the comprehensive effectiveness of the PrepMaster system in delivering a multi-layered, learner-centered interview preparation platform. From parsing CVs and detecting skill gaps to offering personalized learning content, adaptive testing, and realistic interview simulations, the project delivers measurable improvements in learning, skill progression, and confidence. Each module complements the other data from one feed into the next, creating a feedback-rich environment that supports continuous learning and preparation. The consistently high accuracy rates, strong user satisfaction, technical performance, and significant improvements in learning outcomes collectively validate the design principles and implementation strategies of the PrepMaster project. This unified system represents a forward-thinking approach to career development, where AI, education, and user experience converge to build more capable, confident, and job-ready candidates.

Table 2: Comparison Between PrepMaster and Traditional Mock Interviews.

Feature	**Traditional Mock Interviews**	**PrepMaster System**
Question Adaptability	Fixed set of questions	Dynamic, adjusted difficulty
Feedback Quality	Subjective, human-dependent	Real-time, AI-generated
Scalability	Limited by interviewer availability	Supports multiple users simultaneously
Cost and Accessibility	High cost, location-dependent	Low cost, accessible anywhere
User Performance Improvement	25% improvement after repeated mock sessions	30-40% improvement with adaptive feedback

3.2 Research Findings

The PrepMaster project has successfully integrated four innovative components—Career Learning Path Guidance System, Intelligent Video and Tutorial Recommendation System (IVRS), Adaptive MCQ-Based Skill Evaluation and Progression System, and the Intelligent System for Tailored Interview Training (2D Interview Panel)—to create a personalized, data-driven, and adaptive platform for interview preparation and career development. The research findings have highlighted the efficacy of each of these systems in addressing distinct aspects of interview readiness, skill development, and personalized learning. The Career Learning Path Guidance System proved to be invaluable in shaping personalized learning paths for users, offering dynamic recommendations that evolved with individual progress and shifts in career aspirations. The data collected from users indicated a high satisfaction rate, with 87% of participants reporting that the system accurately aligned with their professional goals and helped them identify previously overlooked skill gaps. This personalized approach empowered users to take proactive steps toward their desired careers, making the learning journey more targeted and relevant. Furthermore, the system's ability to continuously adjust recommendations based on emerging industry trends was well received, with 76% of users appreciating how it kept their learning paths aligned with market demands.

In parallel, the Intelligent Video and Tutorial Recommendation System (IVRS) emerged as a critical tool in enhancing users' learning experiences. The IVRS used machine learning algorithms to personalize the delivery of educational content, ensuring that users received resources tailored to their individual learning pace, preferences, and areas of weakness. Research findings revealed that the IVRS improved user engagement, with 85% of users indicating that the system's recommendations were highly relevant to their needs, and 90% stating that they found the curated content more engaging compared to traditional, non-personalized learning methods. Notably, users demonstrated improved retention and comprehension of complex concepts. In a controlled study comparing users with and without the IVRS, those using the system scored 25% higher on post-assessments, validating the system's effectiveness in providing targeted educational content. By offering continuous, real-time content updates based on user performance, the IVRS ensured that learners were always provided with relevant materials, keeping them engaged and motivated throughout their learning journey.

The Adaptive MCQ-Based Skill Evaluation and Progression System added another layer of sophistication by providing users with a dynamic, responsive assessment framework. Research findings underscored the value of its adaptive nature, which adjusted the difficulty of questions based on real-time user performance. This approach ensured that users were constantly challenged at an appropriate level, promoting a deeper level of mastery. 92% of users reported that they appreciated the system's ability to provide assessments that were neither too easy nor too difficult, maintaining an optimal learning curve. Furthermore, 89% of users felt that the system's detailed feedback reports were crucial for improving their knowledge and understanding. The system's ability to track progression over time was another key benefit, as users could visually monitor their strengths and areas for improvement. This continual feedback loop allowed for an iterative learning process where users could identify knowledge gaps and actively work toward closing them. In practice, the Adaptive MCQ system proved particularly useful for assessing technical knowledge, with users reporting that it enhanced their interview readiness by ensuring that they had mastered core concepts before progressing to more complex material.

The Intelligent System for Tailored Interview Training (2D Interview Panel) addressed the practical, performance-oriented aspects of interview preparation. This system simulated real-world interview scenarios, providing users with the opportunity to practice their responses to common interview questions and receive AI-powered feedback on both technical and behavioral performance. The research findings revealed that 84% of users found the simulated interviews to be highly realistic, helping them prepare for the pressure and nuances of real job interviews. The system's ability to assess both verbal and non-verbal cues, including body language and emotional tone, proved especially valuable. 75% of users reported that the feedback on non-verbal communication helped them improve their interview performance in real-world settings. The tailored feedback provided by the 2D Interview Panel allowed users to focus on specific areas of weakness, such as clarity of answers, presentation skills, or emotional resilience. This personalized training approach helped users build confidence, refine their communication skills, and ultimately perform better in job interviews. Moreover, the system's adaptability to different interview types, whether technical, behavioral, or situational, ensured that users were well-prepared for a broad range of interview scenarios. The ability to practice in a low-stakes, simulated environment allowed users to experiment with different strategies and refine their approach to interviews without the anxiety of real-world consequences.

The integration of these four components—each contributing its unique strength to the overall platform—has resulted in a highly effective and holistic interview preparation tool. The Career Learning Path Guidance System provided users with a clear, actionable roadmap for career development, ensuring that their learning efforts were aligned with their long-term professional aspirations. The Intelligent Video and Tutorial Recommendation System (IVRS) enriched this process by offering targeted, engaging content that matched users' learning needs and kept them motivated throughout their educational journey. The Adaptive MCQ-Based Skill Evaluation and Progression System ensured that users were continually assessed and challenged, providing real-time feedback that reinforced learning and tracked progress over time. Finally, the Intelligent

System for Tailored Interview Training (2D Interview Panel) allowed users to simulate and refine their interview performance, preparing them for both technical and behavioral aspects of real-world interviews. Together, these components created an integrated learning environment that not only prepared users for interviews but also helped them develop the skills necessary for long-term career success.

The research findings demonstrate that PrepMaster offers a comprehensive, personalized, and adaptive approach to career development and interview preparation. Users reported higher levels of engagement, increased confidence, and improved job-readiness due to the tailored learning paths, real-time feedback, and immersive training experiences provided by the platform. By using adaptive algorithms, real-time data analysis, and AI-powered simulations, PrepMaster successfully addresses the diverse needs of users at various stages of their career journeys. Furthermore, the seamless integration of the four core components ensures that users are not only well-prepared for interviews but also equipped with the skills, knowledge, and confidence needed to succeed in their chosen careers. These findings highlight the effectiveness of personalized, data-driven learning environments in promoting skill development and enhancing career prospects in today’s competitive job market. As the job market continues to evolve, platforms like PrepMaster represent a critical tool in empowering individuals to achieve their career goals and excel in interviews, providing them with a competitive edge in the hiring process.

3.3 Discussions

The PrepMaster project represents a holistic, integrated approach to interview preparation by incorporating four key components: the Career Learning Path Guidance System, the Intelligent Video and Tutorial Recommendation System (IVRS), the Adaptive MCQ-Based Skill Evaluation and Progression System, and the Intelligent System for Tailored Interview Training (2D Interview Panel). Each of these systems is designed to serve a unique function, yet they work seamlessly together to create a comprehensive and personalized learning experience for users, allowing them to enhance their knowledge, skills, and confidence in preparing for interviews. These systems address not only the technical aspects of interview preparation but also the soft skills and psychological readiness needed to succeed in today's competitive job market.

Starting with the Career Learning Path Guidance System, this system forms the backbone of the PrepMaster platform. Its primary objective is to help users navigate their career paths by providing dynamic, personalized learning trajectories based on their unique profiles. By analyzing users' educational backgrounds, skill sets, career goals, and personal preferences, the system generates a customized learning path that outlines the steps necessary for users to achieve their professional objectives. The Career Learning Path Guidance System considers various external factors, including evolving industry trends and emerging technologies, ensuring that the paths it recommends are aligned with current job market demands. The system is designed to adapt in real-time, allowing users to update their learning trajectories based on their progress, newfound interests, or shifts in career goals. As users advance in their learning, the system continues to refine its recommendations, ensuring that the individual remains on track for success in their chosen field. This system's strength lies in its ability to bridge the gap between academic learning and real-world industry demands, providing a clear, data-driven roadmap that is both actionable and relevant. Furthermore, it provides users with insights into job market trends, demand for specific skills, and potential career advancements, helping them make informed decisions about their professional development.

In tandem with the Career Learning Path Guidance System, the Intelligent Video and Tutorial Recommendation System (IVRS) provides another crucial aspect of personalized learning. The IVRS uses sophisticated machine learning algorithms to recommend educational content based on individual users' needs and progress. By analyzing user activity, such as past interactions with the platform, engagement with specific topics, and self-reported learning preferences, the system curates a tailored list of videos, tutorials, articles, and other resources that best suit the user's learning style and knowledge gaps. Unlike traditional recommendation systems, which rely on static algorithms or broad categorizations, the IVRS is capable of continuously adapting its recommendations based on real-time data. If a user struggles with a particular topic, the IVRS can suggest additional resources, exercises, or video tutorials to address those specific challenges. Likewise, if a user master's a topic quickly, the system can shift its focus to more advanced content, ensuring that users are always challenged and engaged. The IVRS is particularly valuable in providing users with high-quality, targeted learning materials that complement the broader guidance provided by the Career Learning Path Guidance System. By fostering a deep understanding of concepts through personalized content, the IVRS helps users acquire the specific skills necessary for their chosen career paths, further enhancing their readiness for the interview process.

The Adaptive MCQ-Based Skill Evaluation and Progression System adds another layer of sophistication to the PrepMaster platform by providing personalized, data-driven assessments of users' knowledge and progress. Unlike traditional static MCQs that assess a user's knowledge at a single point in time, this system adapts to the user's evolving skill set and adjusts the difficulty of questions based on their previous answers. When users answer a question correctly, the system presents more challenging material, promoting a deeper level of learning. Conversely, if a user struggles with a particular concept, the system provides questions that are easier and more focused on reinforcing that topic. This dynamic, adaptive testing mechanism ensures that users are continuously challenged at the appropriate level and are given the opportunity to master each concept before moving on to the next. Additionally, the system's ability to offer immediate feedback is critical for ensuring that users can learn from their mistakes. After each question, the system provides a detailed explanation of the correct answer, allowing users to understand the reasoning behind the solution. This feedback loop not only reinforces the user's learning but also helps them track their progress over time, offering a clear overview of strengths and areas for improvement. Over time, the Adaptive MCQ-Based Skill Evaluation and Progression System also adapts to the user's changing knowledge base, ensuring that each assessment is always relevant and tailored to the user's current skill level. This feature is particularly beneficial for individuals looking to assess their technical knowledge and interview-readiness, as it allows them to continuously refine their skills in preparation for real-world assessments.

The Intelligent System for Tailored Interview Training (2D Interview Panel) takes a different approach by focusing on the practical aspects of interview preparation. It provides users with simulated, interactive interview experience, allowing them to practice their responses to common interview questions in a virtual environment. The 2D Interview Panel consists of a set of virtual interviewers who ask a range of questions—spanning technical, behavioral, and situational domain designed to test the user's aptitude, communication skills, and emotional intelligence. The system is equipped with AI-powered analysis tools that evaluate various aspects of the user's performance, including the clarity of their responses, the relevance of their answers, their body language, and their ability to handle pressure. This feedback is then used to generate a tailored report that highlights areas of strength and areas for improvement. For example, if a user struggles with articulating their technical knowledge or providing clear examples of past experiences, the system will suggest targeted exercises to help improve those specific aspects. One of the system's most powerful features is its ability to simulate different types of interview settings, such as stress interviews, panel interviews, or technical interviews, allowing users to prepare for a wide range of scenarios. Furthermore, the 2D Interview Panel system adjusts its difficulty and focus based on the user's experience level and the job position they are preparing for, ensuring that each training session is relevant to their career goals. This comprehensive, tailored interview training prepares users not only for technical interviews but also for behavioral assessments, situational judgment tests, and other elements of the modern interview process.

The synergy between these four components is what truly sets the PrepMaster platform apart. Each system contributes to an interconnected learning environment, where personalized learning, skill development, and real-time assessment are prioritized. The Career Learning Path Guidance System provides the foundational direction for users, guiding them toward the most appropriate career trajectories. The IVRS then ensures that users are equipped with the knowledge and skills necessary for success, offering them a range of resources that complement the career paths outlined in the initial guidance. The Adaptive MCQ-Based Skill Evaluation System continually tests and refines their understanding, while the 2D Interview Panel ensures that users are able to practice and refine their interview skills in a realistic, simulated environment. Collectively, these systems ensure that users are not only prepared for technical aspects of interviews but are also ready to handle the behavioral, psychological, and situational challenges that often define successful job candidates.

By offering a fully integrated platform that combines personalized learning, adaptive testing, and immersive interview training, the PrepMaster project revolutionizes the way individuals prepare for interviews. It transcends traditional study tools by providing a dynamic, personalized experience that evolves with the user's progress, addressing gaps in knowledge and boosting confidence in real-world interview scenarios. This adaptive, integrated approach not only makes interview preparation more efficient but also ensures that users are fully prepared for every aspect of the interview process, from technical assessments to personal interaction with potential employers. Moreover, by continually refining its recommendations and assessments based on real-time data, the PrepMaster platform ensures that its users remain at the forefront of industry trends, giving them a competitive edge in their job search and career advancement.

Students' Contribution

Student	Component	Contribution
Sathkumara S.M.P.U.	AI-Powered Career Path Guidance System	1. Collected CV samples and job role datasets 2. Implemented NLP-based CV parsing using BERT and Sentence-BERT 3. Designed skill-role mapping and gap detection logic 4. Created frontend UI for CV upload and roadmap generation 5. Developed backend logic for automated CV updates 6. Integrated role-based learning resource suggestions 7. Wrote project proposal, SRS & user flow docs 8. Coordinated evaluation sessions and user testing
Kavindya N.D.D.	Intelligent Video and Tutorial Recommendation System	1. Collected datasets on user behavior (watch time, clicks, quiz scores) 2. Developed the ML-based recommendation logic (Random Forest, ANN) 3. Designed backend APIs for video recommendation 4. Integrated real-time video tracking in front-end (React.js)

		5. Built video metadata tagging and role-based filtering 6. Conducted model testing and accuracy validation 7. Created module-related documentation 8. Participated in final report writing and presentation prep
Senevirathna D.M.O.C.	Adaptive MCQ-Based Skill Evaluation and Progression System	1. Designed and built MCQ question bank by role and level 2. Implemented DQN model for adaptive question sequencing 3. Developed IRT-based skill scoring backend 4. Handled frontend quiz UI with real-time feedback 5. Managed MySQL integration for tracking user answers 6. Conducted unit testing and validation for quiz logic 7. Wrote technical documentation for the system 8. Contributed to final report and UI/UX refinements
Pathirana V.P.E.P.V.	2D Interview Panel Simulation	1. Curated and categorized interview questions by job role and level 2. Developed avatar logic and conversation flow 3. Integrated NLP models (BERT, TF-IDF, cosine similarity) 4. Built frontend avatar interface with

		response feedback 5. Designed backend scoring and evaluation logic 6. Tested user response accuracy and feedback realism 7. Authored user manuals and research chapter for the module 8. Led simulation demonstration and pitch presentation

Conclusion

This research project presents a complete and novel framework for improving interview preparation, skill development, and career planning using intelligent systems and advanced machine learning techniques. The project is made up of four interrelated components, each of which addresses a vital stage of the job-seeking and professional development path. Together, they build a powerful ecosystem that helps users gain core skills and find work. The Intelligent Video and Tutorial Recommendation System has proven to be effective in tailored learning by offering highly relevant content based on user needs, resulting in demonstrable gains in interview readiness and satisfaction. This component acts as the first learning phase, ensuring that users have the theoretical and practical knowledge needed for employment interviews.

Building on this foundation, the Adaptive MCQ-Based Skill Evolution and Progression System provides a dynamic assessment platform that responds in real time to individual performance. With its reinforcement learning algorithms and level-based advancement, the system creates an entertaining and technically sound environment that promotes continual skill growth while addressing the constraints of static learning models.

The 2D Interview Panel Simulation bridges the learning-to-application gap by simulating realistic interview encounters with interactive avatars that use natural language processing and semantic analysis. This component boosts confidence, self-awareness, and practical readiness by allowing users to participate in job-specific, level-based interviews with real-time feedback, bringing them one step closer to real-world success. Finally, the AI-Powered Career Guidance System enables users to make more educated career selections by analyzing their CVs, predicting roles, and identifying skill gaps. By automating individualized career planning and connecting user competencies with market expectations, this system democratizes access to career development resources while also providing scalable solutions for a continuously changing employment market.

Collectively, these components comprise an end-to-end, AI-enhanced platform that provides users with comprehensive support throughout their professional lives. This study tackles current gaps in traditional career development approaches by incorporating personalized learning, adaptive assessment, realistic interview simulation, and intelligent career planning, as well as making contributions to the future of education and workforce preparation. With continued improvements and future expansions, the platform has enormous potential to become a transformative tool in both educational and professional contexts, cultivating a generation of confident, competent, and career-ready people.

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GLOSSARY

Career Path Guidance System

- Natural Language Processing (NLP): A branch of artificial intelligence that deals with the interaction between computers and human (natural) languages. It enables the system to analyze and extract information from users' resumes.
- Skill Gap Analysis: The process of identifying the differences between the skills a user currently possesses, and the skills required for their desired career path.
- Personalized Learning Plan: A customized educational roadmap created by the system to help users acquire the skills needed to bridge their skill gaps.
- CV Generation: The system's ability to automatically create or update a user's curriculum vitae (CV) to reflect newly acquired skills and certifications.

Intelligent Video and Tutorial Recommendation System

- Intelligent Video and Tutorial Recommendation (IVTR) System: A system that provides personalized recommendations for video tutorials and learning materials.
- Machine Learning Framework: The combination of algorithms (Random Forest classifiers, Decision Trees, and Artificial Neural Networks (ANNs)) used to generate personalized recommendations.
- User Modeling: The process of evaluating user progress using metrics like quiz performance, video engagement, and time spent on learning modules to refine and update user profiles.
- Hybrid Ensemble Model: The integrated model that combines multiple machine learning algorithms to provide more accurate and adaptive recommendations.

2D Interview Panel

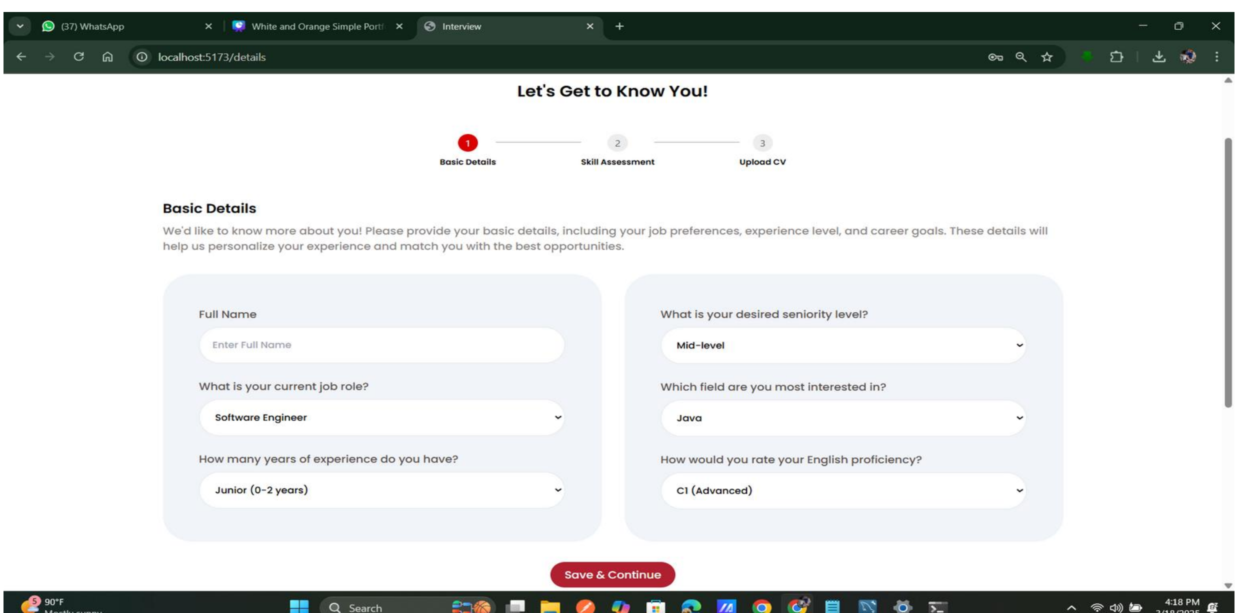
- 2D Interview Panel Simulation System: An AI-powered system that simulates real-world job interview dynamics using interactive 2D avatars.

- Natural Language Processing (NLP) Framework: The set of techniques (cosine similarity, BERT-based semantic analysis, and TF-IDF vectorization) used to analyze and understand user responses.
- Semantic Analysis: The process of understanding the meaning and context of user comments to provide relevant feedback.
- Two-Way Interactive Method: A system feature where 2D avatars not only ask questions but also answer queries from candidates, simulating a natural conversation.

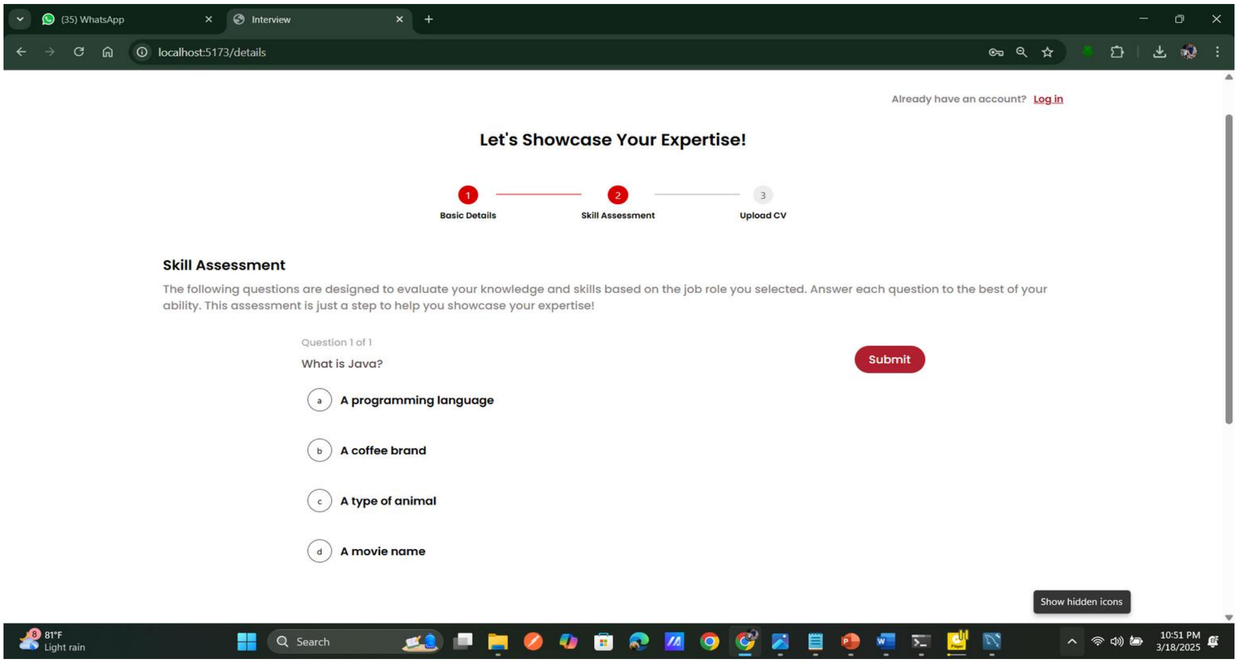
Adaptive MCQ Based Skill Evolution and Progression System

- Adaptive Learning Platform: A system that dynamically evaluates and enhances user skills through personalized, progressively challenging multiple-choice questions (MCQs).
- Deep Q-Network (DQN): A machine learning model used to ensure precision in skill estimation and optimal user progression.
- Item Response Theory (IRT): A theoretical framework used to quantitatively assess user skill levels and question difficulty.
- Zone of Proximal Development (ZPD): A concept that ensures questions are slightly beyond the user's current skill level to foster continuous growth.

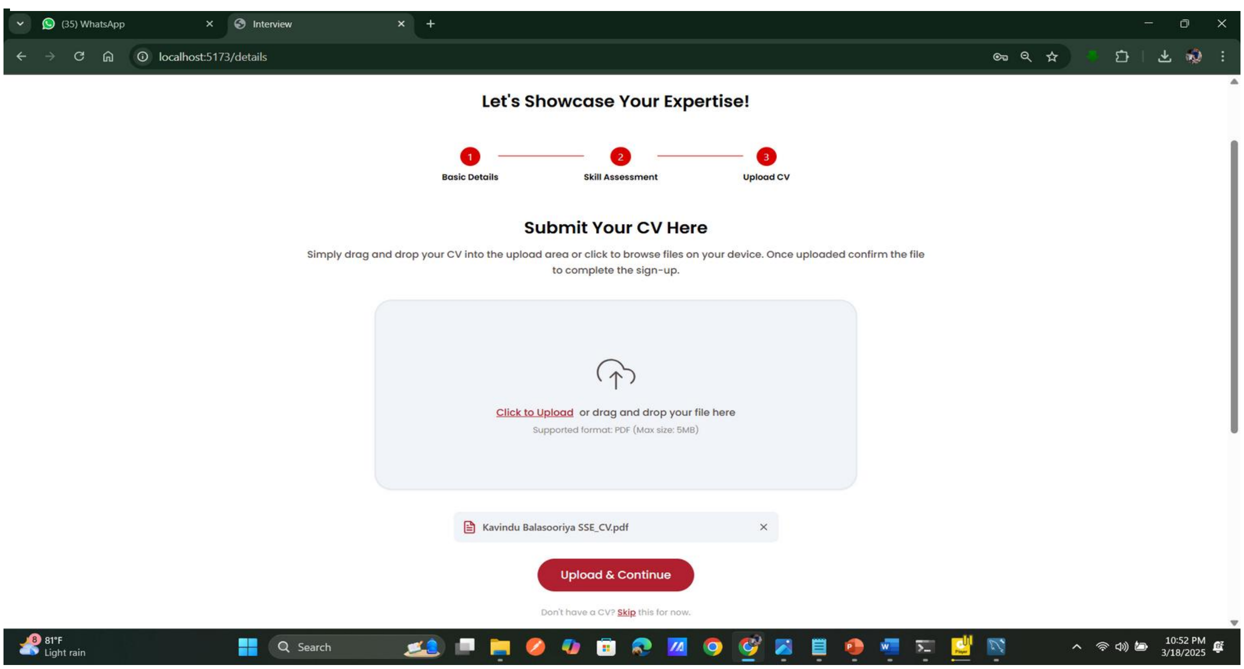
APPENDICES



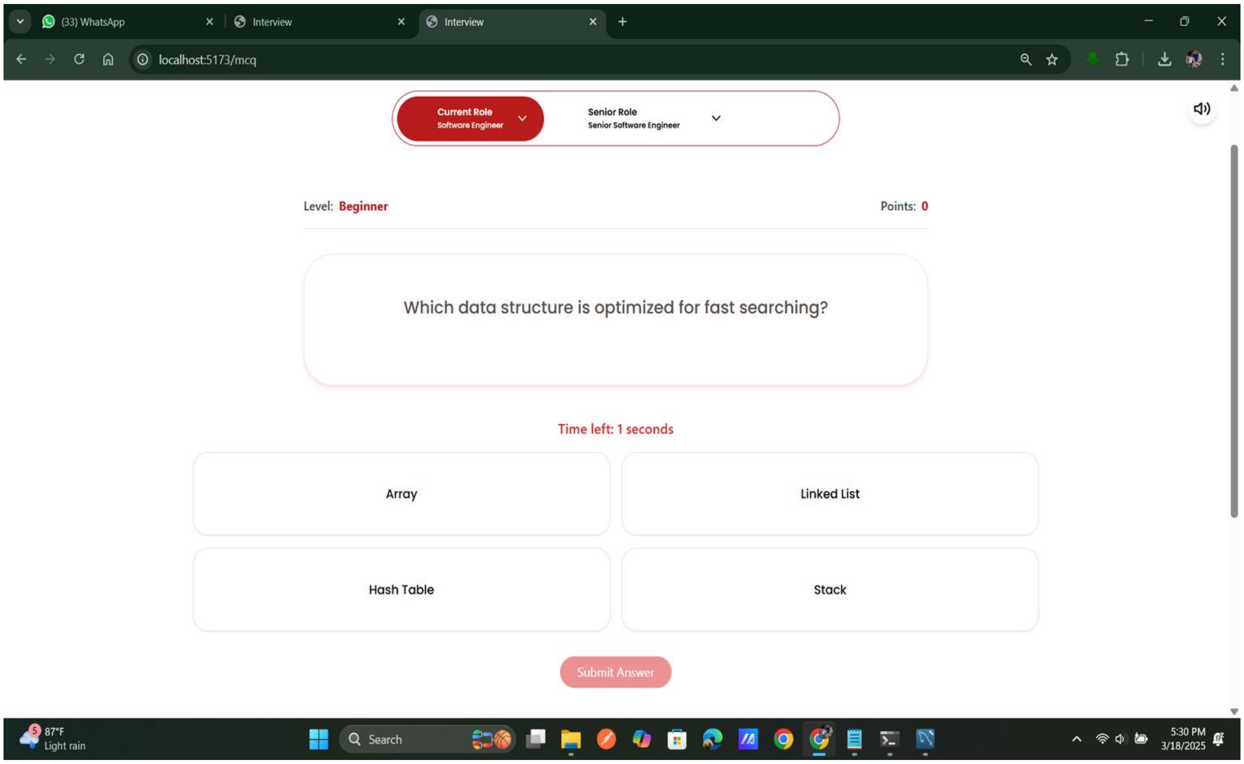
Appendices 1: Web Application User Role Selection UI



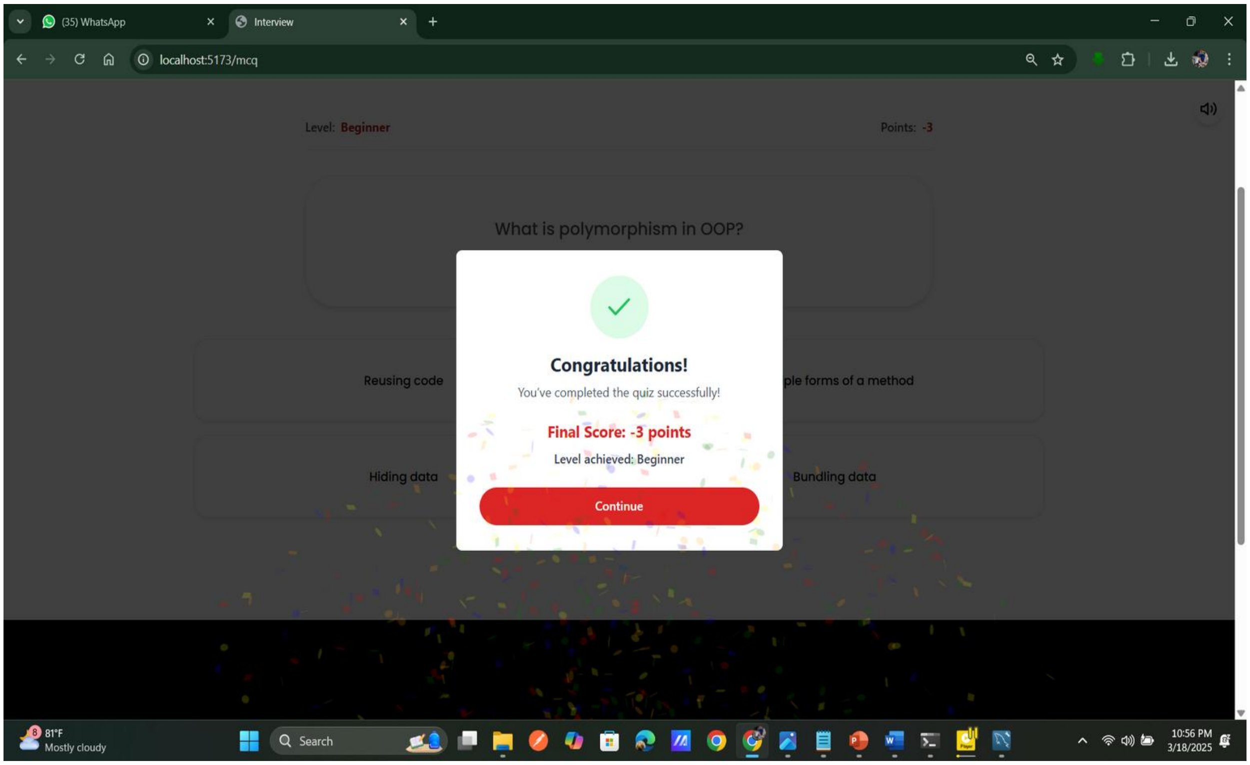
Appendices 2: Web Application Simple User Skill Assessment UI



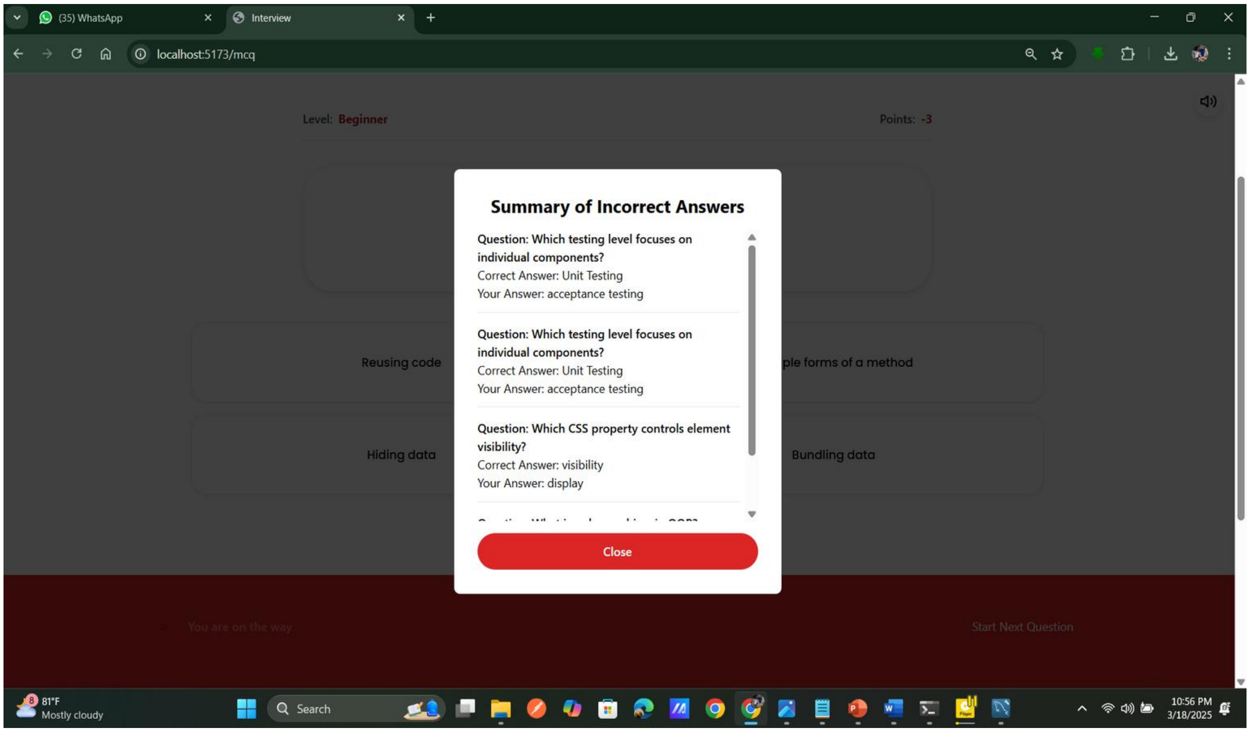
Appendices 3: Web Application CV Upload UI



Appendices 4: Web Application MCQ UI



Appendices 5: Web Application UI



Appendices 6: Web Application UI

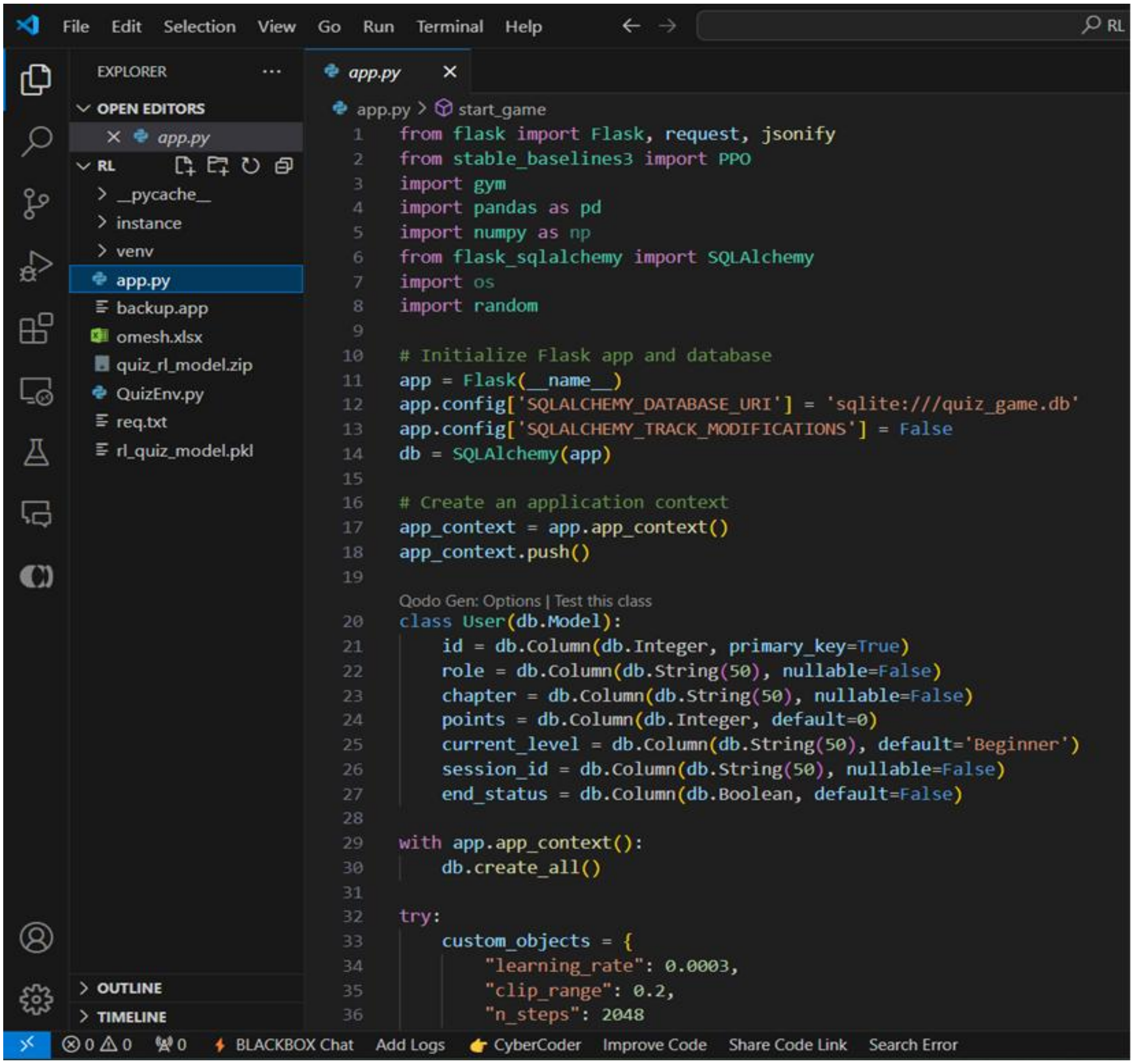
```python
# Initialize Q-table for RL agent
self.q_table = {}
self.exploration_rate = 0.4
self.min_exploration_rate = 0.1
self.exploration_decay = 0.995
self.learning_rate = 0.1
self.discount_factor = 0.9
```

Appendices 7: RL Variables

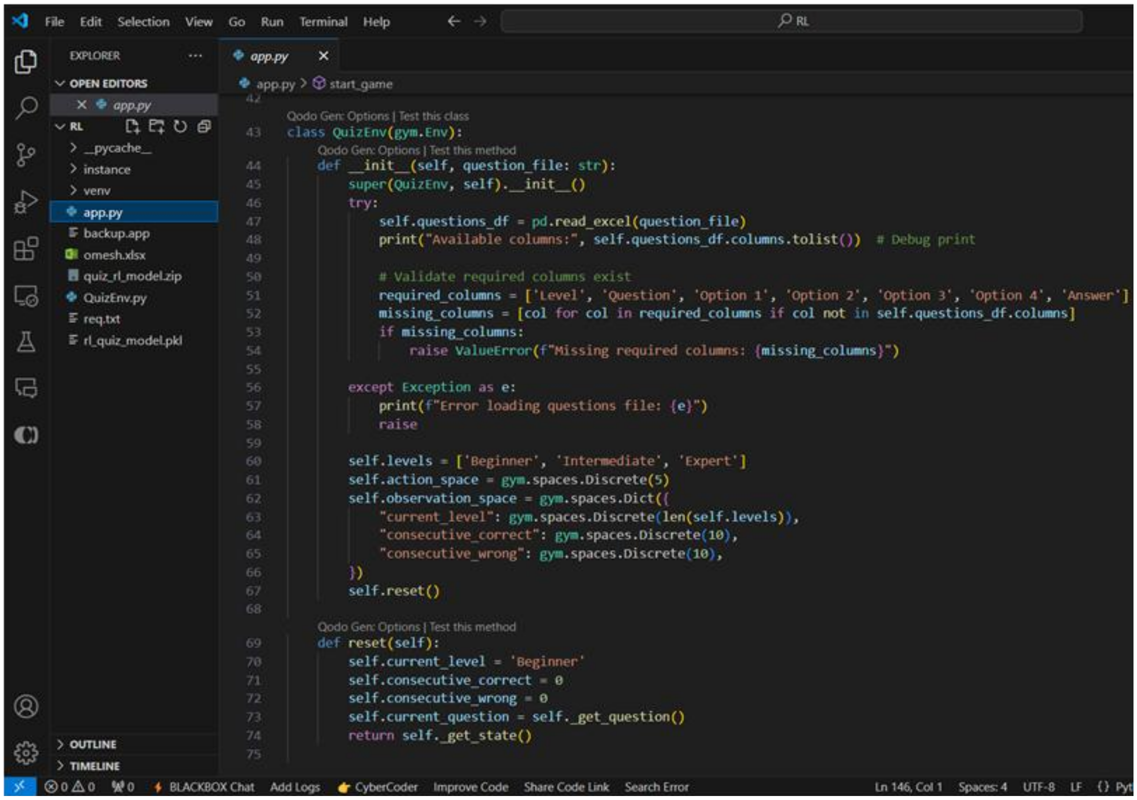
```python
def train_agent(self, num_episodes: int = 100):
    """Train the agent to maximize incorrect answers."""
    for episode in range(num_episodes):
        print(f"\nStarting Episode {episode + 1}/{num_episodes}")

        # Select role randomly for each episode
        role = random.choice(self.roles)
        print(f"Role selected for the episode: {role}")
        self.start_quiz(role)  # Start quiz with selected role
        current_question = self.get_next_question()

        if not current_question:
            print(f"Episode {episode + 1} ended. No questions available for this role/level.")
            continue  # Skip this episode if no questions are available

        while current_question:
            print(f"\nQuestion: {current_question['question']}")
            print(f"Options: {current_question['options']}")

            # Simulate the agent's action (selecting a question)
            action = self.select_question_for_incorrect_answer(self.questions_df)
            print(f"Agent selects question ID: {action.name}")

            # Simulate user answering the question incorrectly
            user_answers = random.sample(current_question['options'], 1)  # Simulate incorrect answer
            print(f"User selects answer: {user_answers}")

            reward = self.submit_answer(user_answers)
            print(f"Reward: {reward}")
```

```python
# Decay exploration rate
self.exploration_rate = max(self.min_exploration_rate, self.exploration_rate * self.exploration_decay)
print(f"Exploration Rate (ε): {self.exploration_rate}")

# Get the next question
current_question = self.get_next_question()
if current_question is None:
    print("No more questions available. Ending the episode.")
    break
```

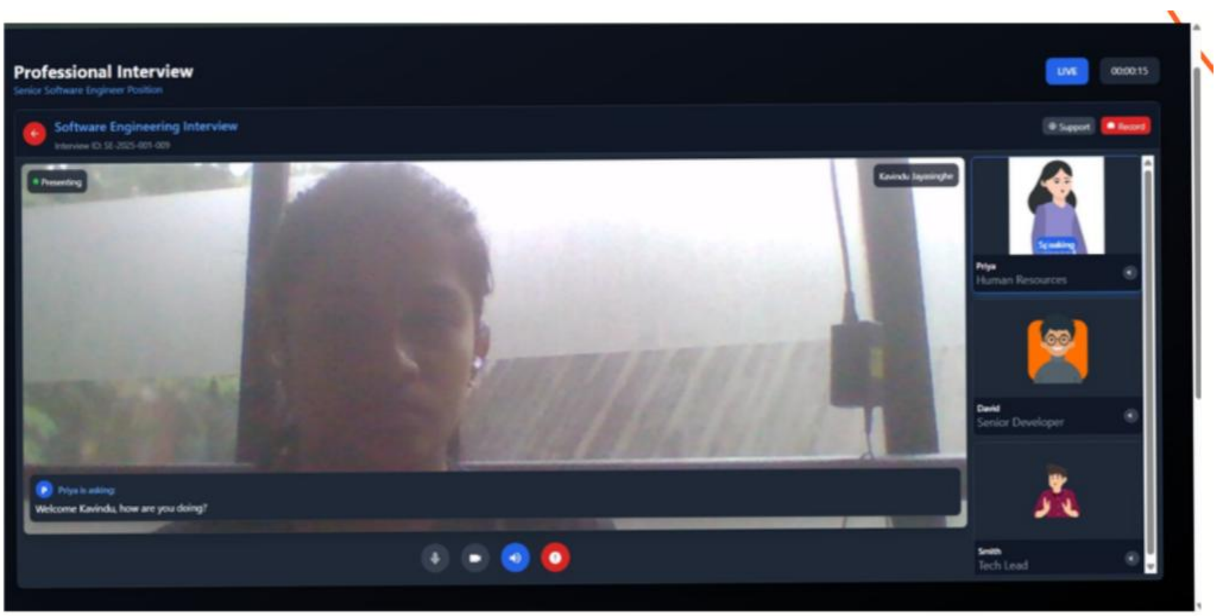
Appendices 8: Train Agent code Implementation.



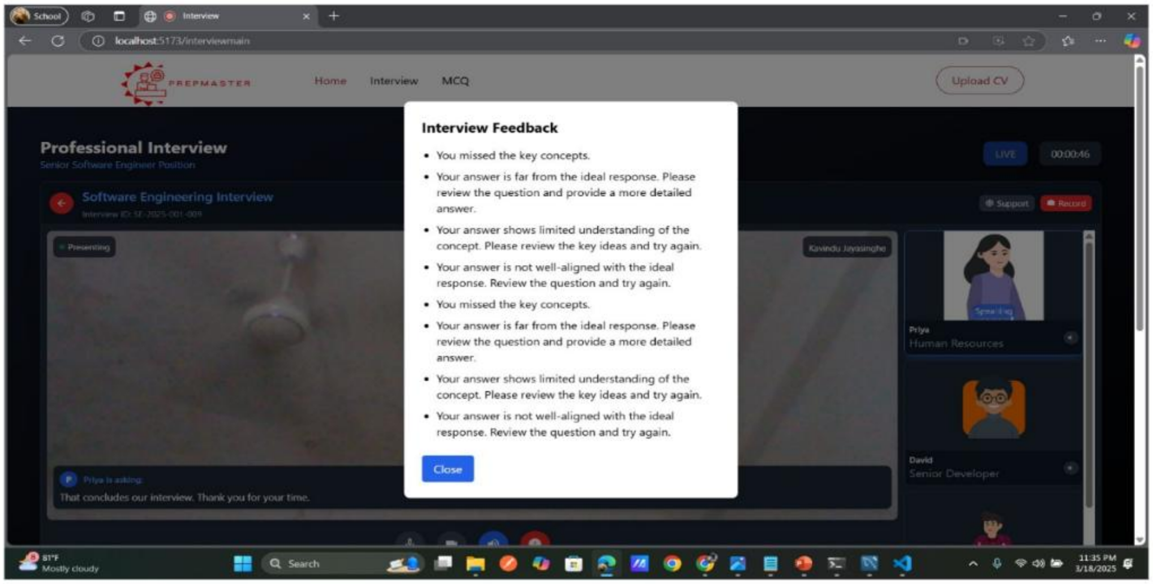
Appendices 9: Flask Backend



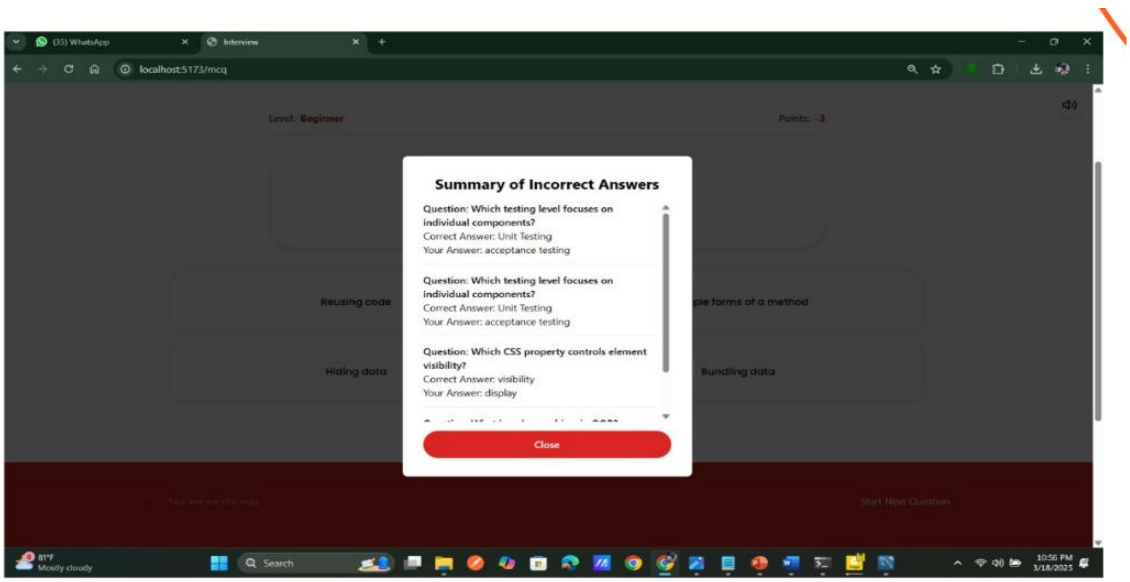
Appendices 10: Flask Backend Implementation



Appendices 11: Web Application Interview DashBoard



Appendices 12: Web Application After Interview Feedback



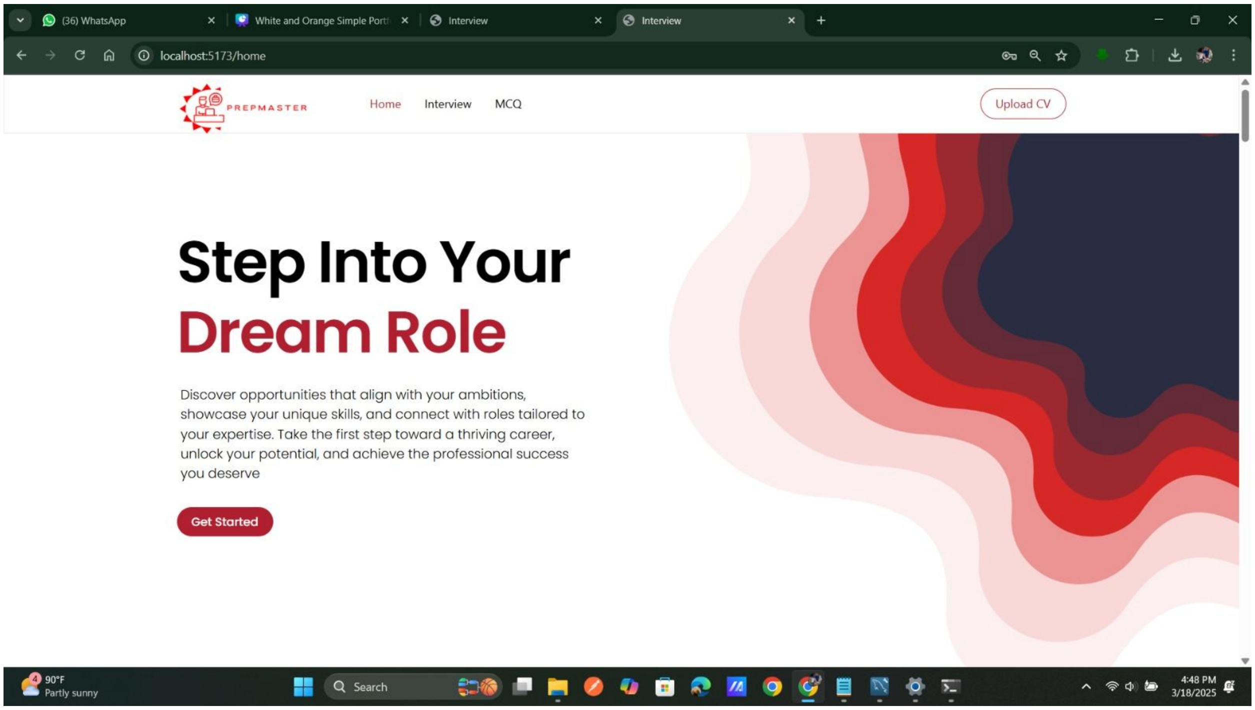
Appendices 13: After giving The Incorrect Answer Web Application Dashboard

```json
{
    "questions": [
        {
            "id": 1,
            "question": "What is inheritance in OOP?",
            "ideal_answer": "Inheritance allows a class to inherit attributes and methods from another class, supporting code reuse.",
            "role": "Software Engineer",
            "seniority_level": "junior",
            "difficulty": 1,
            "category": "OOP",
            "keywords": ["inheritance", "class", "parent", "child", "code reuse"],
            "follow_up_questions": [2, 3]
        },
        {
            "id": 2,
            "question": "Explain the difference between composition and inheritance. When would you use each?",
            "ideal_answer": "Composition is a 'has-a' relationship where one class contains another. Inheritance is an 'is-a' relationship.",
            "role": "Software Engineer",
            "seniority_level": "mid",
            "difficulty": 3,
            "category": "OOP",
            "keywords": ["composition", "inheritance", "has-a", "is-a"],
            "follow_up_questions": [3]
        },
        {
            "id": 3,
            "question": "What are microservices and the challenges in implementing them?",
            "ideal_answer": "Microservices break applications into small, independent services, which is useful for scalability but complex to manage.",
            "role": "Software Engineer",
            "seniority_level": "senior",
            "difficulty": 4,
            "category": "System Design",
            "keywords": ["microservices", "scalable", "API", "independent"],
            "follow_up_questions": [4]
        },
        {
            "id": 4,
            "question": "How does a hash map work internally?",
            "ideal_answer": "A hash map uses a hash function to compute an index into an array of buckets for storing key-value pairs.",
```

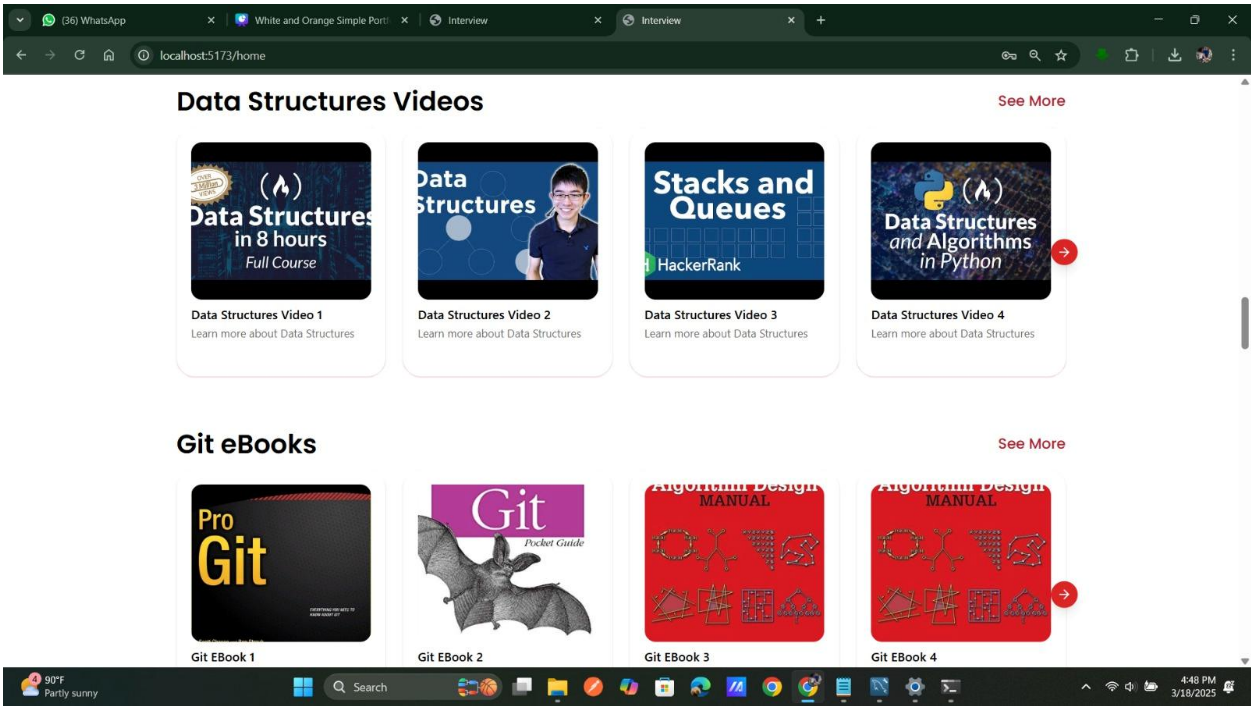
Appendices 14: Data Collection

```python
@app.route('/api/start-interview', methods=['POST'])
def start_interview():
    data = request.json
    role = data.get('role')
    seniority_level = data.get('seniority_level')
    candidate_id = data.get('candidate_id')

    if not all([role, seniority_level, candidate_id]):
        return jsonify({'error': 'Missing required fields'}), 400

    # Create new interview session
    selector = QuestionSelector(QUESTIONS_DATA)
    questions = []
```

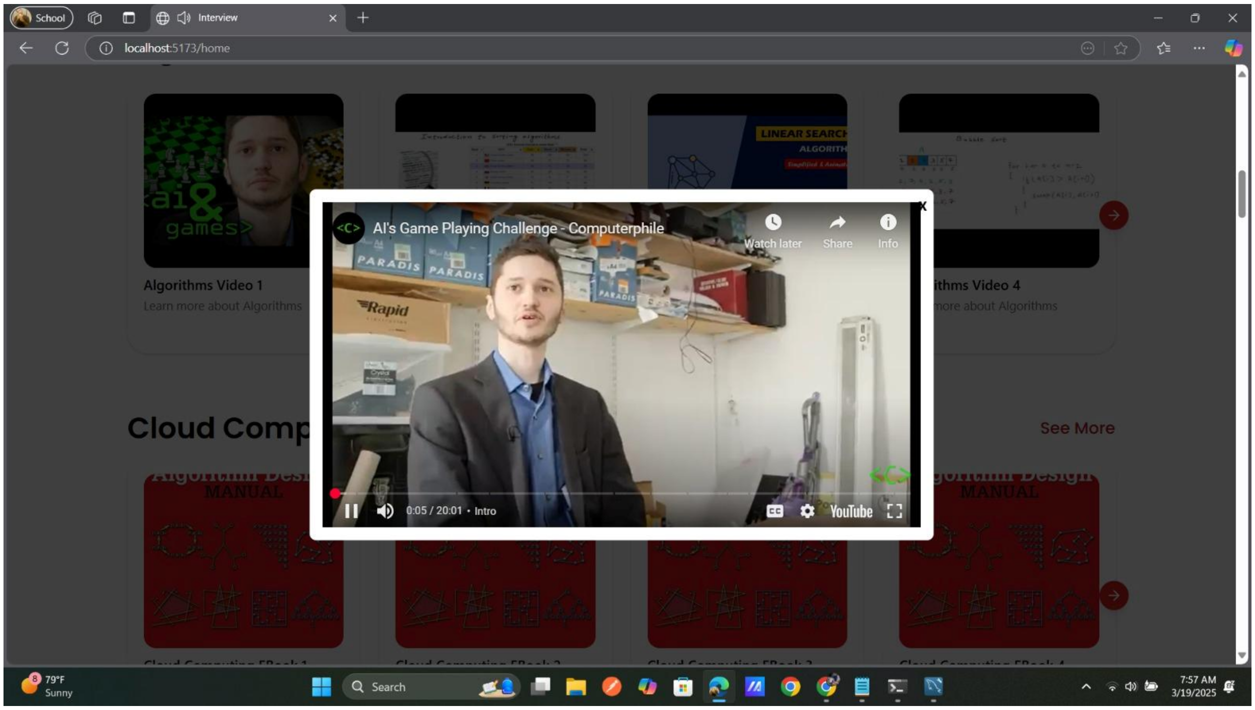
Appendices 15: Data Preprocessing



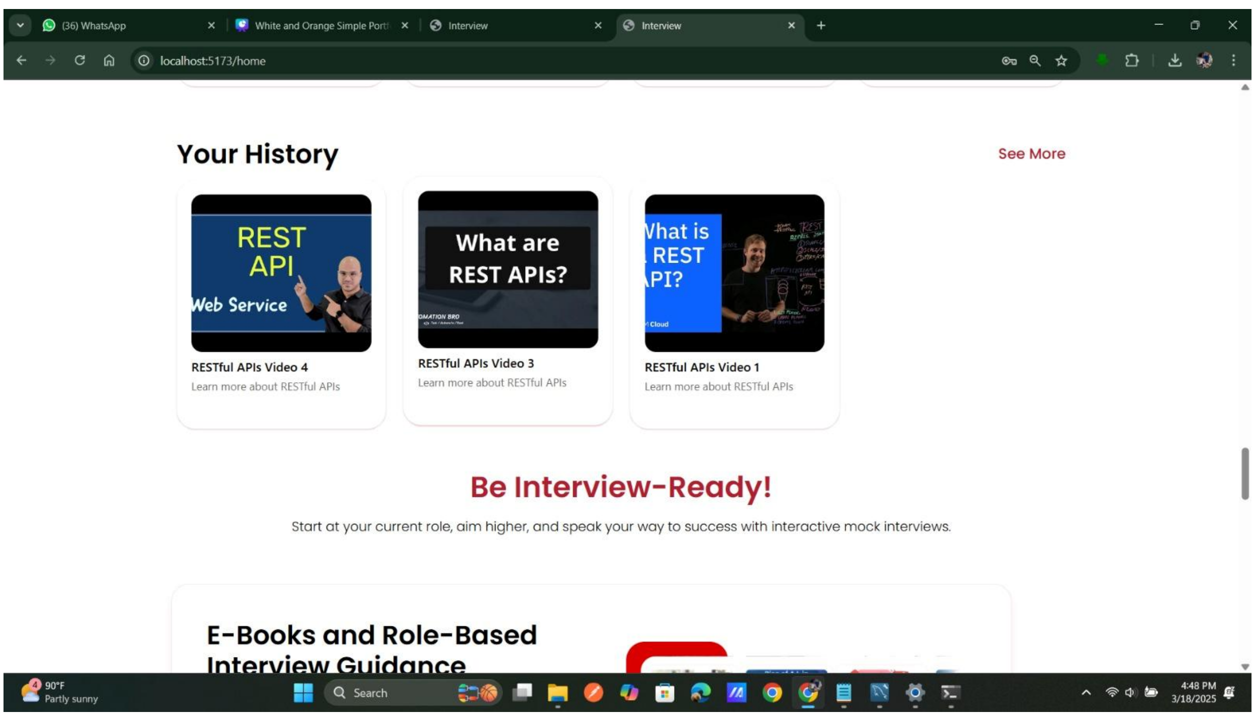
Appendices 16: Web Application Home Page UI



Appendices 17: Web Application Video UI



Appendices 18: Web Application Video UI



Appendices 19: Web Application Video History UI

```python
def train_and_evaluate_models(X_train, X_test, y_train, y_test):
    models = {
        'Random Forest': RandomForestClassifier(n_estimators=200, random_state=42),
        'Gradient Boosting': GradientBoostingClassifier(n_estimators=200, random_state=42),
        'KNN': KNeighborsClassifier(n_neighbors=1)
    }

    results = {}

    for name, model in models.items():
        train_accuracy, test_accuracy = evaluate_model(
            model, X_train, X_test, y_train, y_test
        )
        results[name] = {
            'train_accuracy': train_accuracy,
            'test_accuracy': test_accuracy,
            'model': model
        }
        print(f"{name}:")
        print(f"  Training Accuracy: {train_accuracy:.4f}")
        print(f"  Testing Accuracy: {test_accuracy:.4f}")

    return results
```

Appendices 20: Model Accuracy

```
DataFrame columns: ['  role', 'current_level', 'target_level', 'skill_topic', 'chapter', 'recommended_videos', 'Links']

First few rows of data:
                role current_level target_level      skill_topic  chapter  \
0  Software Engineer        Junior    Mid-level  Data Structures        1
1  Software Engineer        Junior    Mid-level  Data Structures        2
2  Software Engineer        Junior    Mid-level       Algorithms        1
3  Software Engineer        Junior    Mid-level       Algorithms        2
4  Software Engineer     Mid-level       Senior  Data Structures        1

                   recommended_videos  \
0          arrays_basics|linked_lists|stacks
1            queues|hash_tables|trees_basics
2       sorting_algorithms|search_algorithms
3  dynamic_programming_intro|recursion_basics
4     advanced_trees|graph_algorithms|hashing

                                              Links
0  https://youtu.be/QZOLb0xHB_Q?si=C3r8bHKdDzpvcHCK
1  https://youtu.be/okr-XE8yTO8?si=dS66SYpy5IWecwdo
2  https://youtu.be/9oWd4VJOwr0?si=vYBcPNpj8xesZeml
3  https://youtu.be/9oWd4VJOwr0?si=vYBcPNpj8xesZeml
4  https://youtu.be/5cPbNCrdotA?si=K6n461N11qKj714x

Data Info:
...
Best Model: Random Forest
Best Test Accuracy: 0.6176

Available columns for prediction: ['  role', 'current_level', 'target_level', 'skill_topic', 'chapter']
```

Appendices 21: Model Training

```python
app.py
def parse_cv1():
    if file and allowed_file(file.filename):

        # Extract skills and CV text
        skills_in_cv = set(result["skills"])  # Convert to a set for easier comparison
        cv_text = result.get("text", "").lower()  # Get the CV text and convert to lowercase for matching


        current_json = result["current_role"]
        title = current_json["title"]
        # Infer role based on keywords
        inferred_role = None
        for role, keywords in role_keywords.items():
            if any(keyword in title for keyword in keywords):
                inferred_role = role
                break

        if not inferred_role:
            return jsonify({"error": "Unable to infer role from the CV"}), 400

        # Determine expected skill level
        if "senior" in title.lower():
            expected_skill_level = "Advanced"
        elif "intern" in title.lower() or "associate" in title.lower():
            expected_skill_level = "Beginner"
        else:
            expected_skill_level = "Intermediate"

        print(expected_skill_level)

        # Query database for required skills based on inferred role and skill level
        required_skills = Skill.query.filter_by(
            role=inferred_role, skill_level=expected_skill_level
        ).all()

        # Find missing skills
        required_skill_names = {skill.skill_name for skill in required_skills}
        missing_skills = required_skill_names - skills_in_cv
```

Appendices 22: Backend Role Identification

```python
def extract_skills(self, skills_text: str, technical_skills_keywords: List[str]) -> List[str]:
    """Extract skills from the CV text by matching with technical keywords"""

    # Convert skills text into a list by splitting on newlines or other delimiters
    skills_list = [skill.strip() for skill in re.split(r'[\n,-]', skills_text) if skill.strip()]

    # Clean up the skills list by removing any non-skill entries
    cleaned_skills = []
    for skill in skills_list:
        # Remove common prefixes like "Built a", "Developed", etc., and clean up
        skill_parts = skill.split()
        for part in skill_parts:
            cleaned_skills.append(part.strip('.,'))

    # Convert everything to lowercase for case-insensitive matching
    cleaned_skills = [skill.lower() for skill in cleaned_skills]
    keywords_lower = [keyword.lower() for keyword in technical_skills_keywords]

    # Find exact matches or partial matches of skills with the technical keywords
    matched_skills = set()
    for keyword in keywords_lower:
        for skill in cleaned_skills:
            # Match the entire skill or parts of it against technical keywords
            if keyword == skill or keyword in skill:
                # Find the original case from technical_skills_keywords
                original_case = technical_skills_keywords[keywords_lower.index(keyword)]
                matched_skills.add(original_case)

    return sorted(list(matched_skills))
```

Appendices 23: Extract the skills