CareerNova: A Proposed Integrated AI-Powered Framework for Resume Generation, ATS Analysis, Personalized Interview Coaching, And Job Recommendation

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***Abstract*—The transition from academic education to professional employment requires candidates to address multiple interconnected tasks, including resume creation, Applicant Tracking System (ATS)-oriented optimization, interview preparation, and identification of suitable job opportunities. Existing career-support tools generally address these tasks independently, requiring candidates to use multiple platforms and repeatedly provide the same information. This paper presents CareerNova, a proposed integrated artificial-intelligence-based career assistance system that combines four modules: an automated resume maker, ATS-oriented resume evaluation and improvement, personalized interview coaching, and job recommendation. The proposed system maintains a structured candidate profile that is reused across the modules to enable consistent personalization. The resume module employs structured information extraction, large language models, and template-based document generation to create professionally organized resumes from candidate-provided information. The ATS module combines deterministic resume analysis, keyword and structural matching, and semantic similarity using sentence embeddings to evaluate resume–job-description alignment and generate actionable improvement recommendations. The interview module uses resume and job-description information to generate personalized questions and supports text- and speech-based mock interviews, with responses evaluated using speech recognition, natural language processing, and AI-assisted semantic analysis. The job recommendation module combines semantic embeddings with structural matching of skills, education, experience, and keywords to generate job-fit scores and interpretable skill-gap information. The proposed framework demonstrates how deterministic analysis and generative AI can be integrated within a unified career-support pipeline. The proposed architecture is designed to provide candidate-specific resume guidance, ATS-oriented compatibility analysis, interview preparation, and explainable job recommendations. The framework provides a foundation for future prototype development and empirical evaluation involving larger-scale user studies and performance validation.**

***Index Terms*—Career assistance, resume creation, applicant tracking system, ATS optimization, interview preparation, job opportunities, AI-based system, structured candidate profile, resume evaluation, personalized coaching, job recommendation, information extraction, language models, document generation, resume analysis, keyword matching, semantic similarity, sentence embeddings, mock interviews, speech recognition, natural language processing, skill-gap analysis, generative AI, career pipeline, candidate-specific guidance**

I. INTRODUCTION

Digital recruitment has changed the demands placed on job seekers at every stage of the hiring pipeline. Organizations increasingly rely on Applicant Tracking Systems (ATS) and automated screening tools to manage the volume of applications they receive, while candidates are expected to present a well-structured resume, align their profile with a target job description, prepare for a structured interview process, and identify suitable job opportunities from an increasingly fragmented job market. Each of these stages has historically been handled by separate, often manual, methods: candidates write their own resumes with limited professional guidance, use generic keyword checklists to guess at ATS compatibility, prepare for interviews using static question banks or peer mock interviews, and search for jobs by manually browsing multiple platforms. This fragmentation leaves candidates particularly students and early-career applicants without a coherent, end-to-end system that connects these stages together.

This paper presents CareerNova, a proposed system comprising four complementary modules developed as independent but connected components of a single career-support pipeline: an AI-based Resume Maker that generates structured, professionally written resume content from user-supplied information; an AI ATS Score Checker and Resume Improvement module that analyzes an uploaded resume against a target job description and produces a compatibility score with actionable improvement recommendations; a personalized AI Interview Preparation module that generates resume- and job-description-grounded interview questions and evaluates candidate responses through text or speech; and an AI-Based Job Recommendation module that recommends suitable job opportunities based on a candidate's resume, skills, qualifications, and experience.

Each module addresses a distinct, well-documented limitation in existing tools. Traditional resume builders provide templates but require users to manually write and organize content, offering little AI-assisted generation or enhancement. Conventional ATS-checking tools focus narrowly on grammar or formatting rather than measuring true semantic alignment between a resume and a specific job description. Existing interview-preparation resources are largely generic, rarely incorporating a candidate's own resume or a specific job description into question selection. Job recommendation systems, meanwhile, have historically relied on keyword-matching techniques that miss semantic relationships between differently worded but equivalent skills, or on black-box models that cannot explain their own recommendations. The four modules of CareerNova are designed to address these limitations individually while sharing a common technical foundation resume parsing, structured information extraction, and large-language-model-assisted analysis across the pipeline.

The remainder of this document reviews the literature relevant to each of the four modules, organized by module, followed by a consolidated reference list covering all cited works across the system.

II. LITERATURE SURVEY

A. Resume Generation and Parsing (Resume Maker Module)

Artificial Intelligence, Natural Language Processing, and Large Language Models have increasingly been applied to resume and CV processing, including automated resume generation, parsing, skill extraction, and job-oriented CV analysis. Sajid et al. [1] presented a Resume Parsing Framework for E-recruitment that addresses the challenges of extracting information from resumes in different formats, demonstrating the importance of resume parsing for producing structured candidate information. Kalidoss et al. [2] investigated automated resume parsing and ranking using NLP techniques, highlighting the usefulness of automated text processing in recruitment applications.

Sai Surya et al. [3] presented an automated resume screening approach combining NLP and machine learning to improve job matching, demonstrating how resume information can be processed to identify candidate-job relationships. Chandak et al. [4] developed a Resume Parser and Job Recommendation System using Machine Learning, combining resume processing with recommendation functionality. Rajput et al. [5] introduced Career Craft AI, a personalized resume analysis and job recommendation system illustrating the growing use of AI for individualized career assistance. Mishra et al. [6] presented an AI-powered model for intelligent resume recommendation and feedback, and Gupta and Singh [7] developed a recommendation system connecting resume tracking with job suggestions.

Foundational large language model research underpins the AI-assisted generation components of the Resume Maker module. Brown et al. [8] demonstrated the few-shot learning capability of large language models (GPT-3), providing a foundation for AI-assisted generation and refinement of natural-language content, and the Gemini model family [9] provides the multimodal generation capability integrated for producing professional summaries, project descriptions, and experience descriptions within the module. Gautam et al. [10] further investigated resume parsing for talent acquisition and job matching, reinforcing the relevance of automated resume processing within modern recruitment systems.

B. ATS Compatibility Scoring and Resume Improvement Module

Sinha et al. [11] proposed an automated approach for resume parsing and job-domain prediction using machine learning and NLP, demonstrating the value of converting unstructured resume content into structured candidate information as an initial stage before evaluating suitability for a target job. Gan et al. [12] presented an LLM-agent-based framework for automated resume screening, showing that large language models can process natural-language resume content and generate more contextual analysis than exact keyword matching, which supports both compatibility evaluation and personalized improvement suggestions.

M. Gurjar [13] proposed an automated resume screening system using NLP and machine learning to compare candidate resumes against job requirements, closely paralleling the ATS module's approach of identifying relevant skills and keywords and evaluating resume-job alignment. Tarun et al. [14] presented Job Screen AI, an automated resume screening system that evaluates resumes against job descriptions to support candidate identification; the ATS module extends this concept by moreover generating a compatibility score and personalized recommendations covering keywords, skills, content, grammar, readability, and formatting.

C. Personalized Interview Preparation Module

Several studies have explored automated interview analysis, question planning, speech recognition, and AI-assisted response evaluation. An interview-assistant system that selects an optimal set of technical questions for a candidate using a knowledge graph and integer linear programming has been reported in the literature as directly relevant to resume-grounded question personalization, though.

Naim et al. [15] presented a computational framework for predicting job-interview performance using verbal and non-verbal features extracted from interview videos, including speech rate, pauses, facial expressions, and lexical content, showing that multimodal features can support automated interview-performance analysis. Chen et al. [16] studied automated video-interview judgment using a large corpus of online interview videos, analyzing speech content, prosody, and facial expression, though this work is primarily assessment-oriented rather than preparation-oriented. Rasipuram and Jayagopi [17] investigated automatic assessment of communication skill in interview-like settings using lexical, acoustic, and visual features, supporting the use of measurable speech characteristics such as speaking rate, pauses, and fluency as communication indicators.

Reimers and Gurevych [18] introduced Sentence-BERT for semantic similarity and sentence-level representation, useful for comparing candidate responses against expected concepts. Radford et al. [20] introduced Whisper, a robust speech-recognition model trained on large-scale weak supervision, supporting audio-based response transcription. Brown et al. [8] (see Section II-A) additionally underpins the module's LLM-based question generation and evaluation capability, and Wei et al. [21] demonstrated Chain-of-Thought prompting for structured reasoning in large language models, relevant to prompt engineering for structured LLM output.

Devlin et al. [25] introduced BERT, and Vaswani et al. [26] introduced the Transformer architecture underlying both BERT and Sentence-BERT, forming the foundational NLP architecture referenced across the module.

Waghmare et al. [23] presented an interactive AI chatbot for job-interview preparation that allows real-time interaction between the chatbot and the candidate during a simulated interview. Their system addresses two limitations they identify in earlier chatbot-based tools: fixed, predefined question sequences that do not respond to a candidate's actual answers, and the inability for a candidate to ask questions back during the interview. This supports the case for adaptive, two-way interaction in interview preparation. However, the system does not incorporate resume analysis or job-description context to personalize question selection.

Maharajpet and Dhananjaya [22] presented a hybrid NLP and transformer-based system that generates personalized interview questions directly from a candidate's resume. Their system identifies key resume sections such as skills, education, projects, and certifications, and uses a fine-tuned FLAN-T5 model to generate five to ten questions per resume, with fallback methods used when a section is missing or unclear. Their evaluation reported over 85% question relevance across a range of resumes. However, the system focuses on question generation from static resume text and does not support interactive delivery or spoken-response evaluation.

Panchal et al. [24] studied automatic question generation from general text documents, combining a machine-learning classification-based Fill-in-the-Blank generator with a rule-based approach for Wh-type questions. Their system also includes a question-evaluator module, and generated Wh-type questions were evaluated using BLEU score against human-authored questions. This supports the feasibility of automated, evaluated question generation more broadly. However, the work targets general reading-comprehension text rather than resumes or job descriptions and does not address interview-specific personalization.

Collectively, this literature supports individual components resume-based question selection, video-interview analysis, speech-based communication assessment, semantic similarity, and speech recognition but limited prior work integrates these into a single personalized framework combining resume analysis, job-description context, adaptive question generation, interactive mock interviews, and explainable feedback, motivating the proposed Interview Preparation module.

D. Job Recommendation Module

Content-based filtering compares candidate attributes directly against job requirements and works without historical interaction data but cannot recommend beyond what is already present in a profile [37]. Collaborative filtering learns from collective user behavior and can surface unexpected recommendations but suffers from the cold-start problem for new users and postings [35, 37]. Knowledge graphs support path-based reasoning over skills, roles, and industries but are static by nature, while transformer-based models such as BERT capture contextual semantics and bridge the vocabulary gap between job seekers and recruiters, at the cost of computational complexity and reduced transparency [17].

Schmitt et al. [36] proposed Majore, a hybrid system that trains a neural network to emulate collaborative-filtering representations from textual features alone, improving cold-start performance for job-CV matching. Dave et al. [30] jointly embedded jobs and skills across three complementary graphs job transition, job-skill, and skill co-occurrence to generate interaction-like representations even for previously unseen jobs. El-Deeb et al. [31] combined BERT-based summarization with Cross-Encoder semantic scoring and XGBoost ensemble learning to capture both deep contextual and structural features such as seniority and skill count.

Explainability is treated in this literature as a requirement rather than an optional feature for responsible deployment in hiring contexts [36]. Post-hoc methods such as SHAP and LIME approximate model behavior through global and local feature attribution respectively, while attention-based explanations are not always faithful to a model's actual decision process; rule-based and natural-language-generation approaches produce more direct, human-readable rationales at the cost of some rigidity. For recruiters, explainability accelerates decisions and builds confidence; for candidates, it converts an opaque ranking into actionable feedback for example, identifying specific missing skills rather than an unexplained score.

Despite this progress, unified architectures combining semantic understanding, structured features, and multi-layered explanation remain scarce [27, 37], traceability of data versions and hyperparameters for audit purposes receives comparatively little attention [27], and most systems treat candidate preferences as static rather than evolving over time gaps that motivate the proposed Job Recommendation module.

III. PROBLEM STATEMENT

The transition from academic education to professional employment presents multiple challenges for students and fresh graduates. While candidates often possess relevant qualifications, technical skills, and project experience, they face difficulties in presenting these effectively across the career pipeline:

- *Resume Creation:*

Manual resume preparation requires candidates to select layouts, organize sections, and write professional descriptions. This often results in grammatical errors, weak project narratives, inconsistent formatting, and excessive effort. Existing resume builders provide templates but lack AI-driven content generation, leaving candidates with resumes that fail to highlight their strengths.

- *ATS Compatibility:*

Applicant Tracking Systems (ATS) filter resumes based on keywords, structure, and alignment with job descriptions. Many candidates are unaware of ATS requirements, leading to resumes that miss critical keywords, skills, or formatting standards. This reduces their chances of passing initial screening despite having relevant qualifications.

- *Interview Preparation:*

Conventional preparation methods such as generic question banks or peer practice lack personalization. They fail to consider the candidate's resume, target company, or job description, resulting in irrelevant preparation. Candidates also lack structured feedback on communication, fluency, and technical accuracy.

- *Job Recommendation:*

Traditional job-matching systems rely on keyword overlap, ignoring contextual semantics and deeper skill-job relationships. They often function as opaque black-box models, leaving candidates uncertain about why a recommendation was made. This reduces trust and fails to highlight actionable skill gaps. Thus, there is a need for a proposed integrated CareerNova that combines resume generation, ATS scoring, interview preparation, and job recommendation into a unified framework. This system should reduce manual effort, improve resume quality, enhance interview readiness, and provide transparent, explainable job recommendations.

IV. OBJECTIVES

The primary objective of this research is to propose and design an AI-based integrated career-assistance framework that supports students and job seekers in resume preparation, ATS-oriented analysis, interview preparation, and personalized job recommendation.

The system integrates multiple modules to achieve the following goals:

- To automate the resume creation process by generating professional content based on user input such as education, skills, and experience. It enables users to select templates, edit content, and download ATS-optimized resumes.
- To develop a deterministic and semantic resume–job matching mechanism that produces an interpretable compatibility score and identifies skill and content gaps.
- To develop a personalized interview coaching workflow that generates resume- and job-description-grounded questions and evaluates candidate responses using textual and speech-based features.
- To match candidates with suitable job openings based on their skills, education, and experience. It provides a fit-score analysis and actionable recommendations for skill enhancement.

V. PROPOSED METHODOLOGY

The proposed CareerNova is a proposed integrated artificial-intelligence-based career preparation system comprising four major functional modules: *AI Resume Maker, AI ATS Score Checker and Resume Improvement, AI Interview Preparation, and AI-Based Job Recommendation*. The system combines document processing, rule-based analysis, natural language processing (NLP), semantic embeddings, large language models (LLMs), and speech recognition to provide personalized career assistance.

The overall methodology follows a modular pipeline in which the candidate's resume acts as the primary source of personalization. Depending on the selected functionality, the system either generates a new resume, analyzes an existing resume, prepares the candidate for a target interview, or evaluates the compatibility between the candidate profile and available job opportunities.

A. AI-Based Resume Generation

The AI Resume Maker enables candidates to create a professional resume without manually constructing each resume section.

1) Candidate Information Collection

The process begins with the collection of candidate information, including:

- Personal and contact information
- Career objective or professional summary
- Educational qualifications
- Technical and soft skills
- Academic and personal projects
- Internships and work experience
- Certifications
- Achievements
- Languages and other relevant information

The collected information is validated and organized according to predefined resume sections.

2) AI-Based Content Generation

The structured information is provided to the AI processing component to generate concise and professionally formatted content for relevant resume sections. The generated content is grounded in the information supplied by the candidate to minimize the introduction of unsupported qualifications or experiences.

The generated content may include professional summaries, project descriptions, experience descriptions, and skill-related statements.

3) Resume Template and Design Selection

After content generation, the candidate selects an appropriate resume design.

The proposed design options include variations in:

- Photograph inclusion
- Themes
- Layouts
- Visual styles
- Section arrangements

The selected template determines the visual organization of the generated content.

4) Resume Generation and Validation

The generated content is combined with the selected template to produce the complete resume.

A preview is presented to the candidate, allowing the information to be reviewed and modified before finalization.

B. AI ATS Score Checker and Resume Improvement

The ATS analysis module evaluates the compatibility and quality of an existing resume with respect to a target job description. The process combines document extraction, structured information extraction, deterministic scoring, semantic matching, and AI-generated improvement recommendations.

1) Resume Upload and Document Processing

The candidate uploads an existing resume in a supported document format. For PDF documents, *PyMuPDF* is proposed for text extraction, while *python-docx* is proposed for DOCX documents. For scanned or image-based resumes, *Tesseract OCR* is applied to obtain machine-readable text.

The extracted information may include:

- Candidate details
- Professional summary
- Skills
- Education
- Work experience
- Projects
- Certifications
- Achievements

The extracted text is subsequently passed to the preprocessing and analysis stages.

2) Resume Structure and Quality Analysis

The system performs deterministic checks on the extracted resume content. These checks identify the presence and quality of important resume components, including contact information, skills, education, experience, and projects.

Additional checks can identify:

- Missing resume sections
- Weak or vague descriptions
- Grammar issues
- Insufficient technical details
- Missing measurable outcomes
- Keyword deficiencies
- Formatting-related issues

A rule-based scoring mechanism is used wherever the evaluation can be performed deterministically. This reduces unnecessary dependence on LLM-generated numerical scores and makes the resulting evaluation more interpretable.

3) Job Description Analysis

The target job description is processed to identify important requirements, including:

- Required technical skills
- Preferred skills
- Educational qualifications
- Experience requirements
- Technologies and tools
- Job responsibilities
- Role-specific terminology

The extracted job requirements form the reference against which the candidate's resume is evaluated.

4) Semantic Resume–Job Matching

To capture semantic relationships beyond exact keyword matching, the system generates vector representations of the resume and job description using *sentence-transformers* with the *BAAI/bge-small-en-v1.5* embedding model.

Let the resume embedding be represented by (E_R) and the job-description embedding by (E_J). Their semantic similarity is calculated using cosine similarity:

$$S_{\text{semantic}} = \frac{E_R \cdot E_J}{\|E_R\| \|E_J\|} \quad (1)$$

The resulting semantic similarity represents the degree of contextual alignment between the candidate's profile and the target job.

The embeddings are stored using *pgvector* within PostgreSQL, enabling vector-based similarity operations without requiring a separate vector database.

5) Structural Matching

In addition to semantic similarity, the system calculates deterministic sub-scores based on structured resume and job-description information.

These include:

- Skills Match
- Experience Match
- Education Match
- Keyword Match

The combined job-fit score can be represented conceptually as:

$$S_{\text{struct}} = w_s S_{\text{skill}} + w_e S_{\text{experience}} + w_d S_{\text{education}} + w_k S_{\text{keyword}} \quad (2)$$

Where:

- S_{skill} = skill-match score
- $S_{\text{experience}}$ = experience-match score
- $S_{\text{education}}$ = education-match score
- S_{keyword} = keyword-match score
- w_s, w_e, w_d, w_k = corresponding weights

Then Add:

$$w_s + w_e + w_d + w_k = 1 \quad (3)$$

where each (S_i) represents an individual matching component and (w_i) represents its corresponding weight.

The weights are configured according to the importance assigned to each component. Missing skills are separately identified by comparing the required skill set with the candidate's extracted skill set.

Importantly, a missing skill indicates that the skill was not detected in the uploaded resume and does not necessarily establish that the candidate does not possess that skill.

6) ATS Score and AI Improvement

The matching results are converted into an ATS-oriented compatibility score. The AI component subsequently analyzes the resume content and generates personalized recommendations.

The improvement recommendations address areas such as:

- Missing or relevant keywords
- Technical skill representation
- Weak bullet points
- Grammar
- Readability
- Project descriptions
- Experience descriptions
- ATS-oriented improvements

Algorithm 1: Resume-to-Job Matching

Input: Resume R, Job Description J

Output: Job-Fit Score Sfit, Skill Gaps G

1. : Extract text from R and J
2. : Extract structured candidate information from R
3. : Extract job requirements from J

4. : Identify candidate skills and required job skills
5. : Compute skill-match score S_{skill}
6. : Compute keyword-match score $S_{keyword}$
7. : Compute experience-match score $S_{experience}$
8. : Compute education-match score $S_{education}$
9. : Generate embeddings E_R and E_J
10. : Compute semantic similarity $S_{semantic}$
11. : Calculate weighted job-fit score S_{fit}
12. : Compare required skills with candidate skills
13. : Identify missing or insufficiently represented skills
14. : Generate improvement recommendations
15. : Return S_{fit} and G

C. AI Interview Preparation

The AI Interview Preparation module provides personalized interview practice using the candidate's resume and selected interview context. The methodology consists of resume intelligence, interview-context processing, personalized question generation, interactive mock interviews, response analysis, adaptive follow-up generation, and feedback generation.

1) Dual-Mode Interview Preparation

The system supports two primary preparation modes:

a) Company/Campus-Specific Preparation

The candidate selects a target company or campus recruitment process. Relevant historical interview-question information, where available, is analyzed according to company, role, question category, difficulty, and frequency.

Historical questions are treated as preparation references rather than guaranteed predictions of future interview questions.

b) Job Description-Based Preparation

The candidate provides a job description along with the resume. The system analyzes the description to identify required skills, technologies, qualifications, responsibilities, and role expectations.

These requirements are compared with the candidate profile to generate role-specific questions.

In both modes, the resume serves as the primary personalization source.

2) Resume Intelligence and Candidate Profile

The uploaded resume is processed to generate a structured candidate profile containing information such as:

- Education
- Technical and soft skills
- Projects
- Certifications
- Achievements
- Internships
- Work experience

The structured profile is reused across question generation, job-description matching, response evaluation, and preparation recommendations.

The system also identifies potential weaknesses in the resume, such as vague project descriptions, missing information, weak technical explanations, or insufficient measurable outcomes. These observations are proposed to improve preparation without modifying the factual information provided by the candidate.

3) Interview Context Processing

For company-specific preparation, historical questions are normalized and organized using attributes such as company, role, category, difficulty, and frequency. Duplicate or highly similar questions are reduced using text normalization and semantic similarity.

For job-description-based preparation, the system extract's role requirements and compares them with the candidate profile.

Requirements are classified as:

- Matched
- Partially matched
- Not detected

The "not detected" category indicates that a requirement was not identified in the uploaded resume and does not necessarily indicate the candidate's actual lack of that skill.

4) Personalized Question Generation

Interview questions are generated and ranked using multiple information sources:

- Candidate resume
- Job-description requirements
- Company-specific interview patterns
- AI-generated practice questions

The questions can belong to several categories, including:

- Technical
- Coding
- Project-based
- HR
- Behavioral
- Aptitude
- Company-specific
- Role-specific

A conceptual question-ranking function is defined as:

$$Q_{score} = \alpha F + \beta R + \gamma C + \delta D + \epsilon Q \quad (4)$$

Where:

- F = historical question frequency
- R = resume relevance
- C = company-context relevance
- D = job-description relevance
- Q = question quality/diversity
- $\alpha,\beta,\gamma,\delta,\epsilon$ = corresponding weights

$\alpha+\beta+\gamma+\delta+\epsilon=1$

The system also maintains question provenance, identifying whether a question is historical, resume-derived, job-description-derived, AI-generated, or hybrid. This prevents AI-generated questions from being incorrectly represented as previously asked company questions.

Algorithm 2: Personalized Interview Question Generation

Input: Candidate Profile P, Job Description J, Interview Context C

Output: Ranked Question Set Q

1.: Extract skills, projects, education and experience from P
2.: Extract requirements from J, if available
3.: Identify matched and not-detected requirements
4.: Retrieve relevant historical questions, if available
5.: Generate personalized questions using candidate and role context
6.: Calculate relevance features for each question
7.: Compute question score Q_{score}
8.: Remove duplicate or highly similar questions
9.: Assign question provenance
10.: Rank questions in descending order of Q_{score}
11.: Return ranked question set Q

5) AI-Powered Mock Interview

The mock interview module provides two modes:

- *Practice Mode:* Candidates review relevant questions, concepts, and preparation points.
- *Interactive Mock Interview Mode:* Candidates respond to dynamically presented questions using text or audio.

For audio responses, the recorded speech is converted into text using speech-recognition models. The resulting transcript is then processed by the response-evaluation pipeline.

6) Speech and Response Analysis

Candidate responses are evaluated using speech recognition, NLP, semantic analysis, and LLM-assisted evaluation.

The evaluation considers:

- Relevance
- Completeness
- Technical concept coverage
- Grammar
- Fluency
- Filler-word usage
- Repetition
- Answer structure
- Technical correctness

For technical questions, the system evaluates aspects such as definition, explanation, example, and practical application.

For behavioral questions, the response can be analyzed according to the *STAR framework: Situation, Task, Action, and Result.*

Technical correctness is not determined solely through semantic similarity. The evaluation considers expected concepts, covered concepts, missing concepts, incorrect statements, and contradictions.

A response score can be represented as:

$$ResponseScore = \sum_{i=1}^{n} w_i S_i$$

where (S_i) represents an individual evaluation dimension and (w_i) represents its corresponding weight. The weights are adjusted according to the question type.

For example, technical questions assign greater importance to concept accuracy, whereas behavioral questions emphasize relevance, structure, and communication quality.

7) Adaptive Follow-Up Question Generation

The system adapts the subsequent interview question according to the candidate's previous response.

A strong response can result in a deeper or more advanced question, whereas an incomplete response can result in a clarification or foundational question.

Follow-up questions can be generated to:

- Clarify an incomplete answer
- Test an uncovered concept
- Identify a misunderstanding
- Relate the response to a candidate project
- Increase question difficulty

Previously asked questions are tracked to minimize unnecessary repetition.

8) Feedback and Preparation Analytics

After each response, the system generates structured feedback rather than relying solely on a numerical score.

Feedback includes:

- Correctly explained concepts
- Missing concepts
- Incorrect or unclear statements
- Grammar and fluency observations
- Answer-structure recommendations
- Areas requiring improvement

At the end of the interview session, the system aggregates performance across questions and identifies recurring weaknesses. These weaknesses are used to recommend targeted practice. For example, repeated difficulties in SQL can result in additional practice focused on joins, aggregation, subqueries, and normalization.

D. AI-Based Job Recommendation

The job-recommendation module extends the candidate profile and resume-analysis pipeline to identify job opportunities aligned with the candidate's skills, qualifications, experience, and preferences.

Where direct job-listing data is available, the system processes legitimate job sources. The initial design also supports direct user-provided job descriptions, which avoids dependence on unauthorized scraping of job-board platforms.

1) Job Data Collection and Preprocessing

The primary input consists of job descriptions provided by the user. Job listings obtained through legitimate APIs can also be processed when available.

Each job description is processed to identify:

- Job title
- Required skills
- Preferred skills
- Educational qualifications
- Experience requirements
- Technologies
- Responsibilities
- Role-specific terms

The candidate resume is processed using the same document-processing pipeline described in Section 5.2.

2) Feature Extraction

Two categories of signals are extracted.

- *Semantic Features:* Resume and job-description text are represented using sentence embeddings generated through *BAAI/bge-small-en-v1.5*.
- *Structural Features:* Deterministic comparisons are performed for skills, education, experience, and keywords.

This combination allows the system to capture both semantic relationships and explicit requirement matches.

3) Job-Fit Calculation

The semantic similarity and structural matching scores are combined to generate a composite job-fit score:

$$S_{fit} = w_{skill}\, S_{skill} + w_{keyword}\, S_{keyword} + w_{semantic}\, S_{semantic} + w_{experience}\, S_{experience} + w_{education}\, S_{education}$$

With

$$\mathbf{w}_{\text{skill}} + \mathbf{w}_{\text{keyword}} + \mathbf{w}_{\text{semantic}} + \mathbf{w}_{\text{experience}} + \mathbf{w}_{\text{education}} = \mathbf{1}$$

For example, only if these are your real weights:

$$S_{\text{fit}} = \mathbf{0.30S}_{\text{skill}} + \mathbf{0.20S}_{\text{keyword}} + \mathbf{0.25S}_{\text{semantic}} + \mathbf{0.15S}_{\text{experience}} + \mathbf{0.10S}_{\text{education}} \quad (4)$$

The system separately identifies missing or insufficiently represented skills. These results are presented to the candidate along with the job-fit score.

Algorithm 3: Job Recommendation Ranking
Input: Candidate Profile C, Job Set J
Output: Ranked Job List J*
1. : For each job j in J do
2. : Extract required and preferred skills
3. : Extract education and experience requirements
4. : Generate candidate and job embeddings
5. : Calculate semantic similarity
6. : Calculate skill-match score
7. : Calculate keyword-match score
8. : Calculate education-match score
9. : Calculate experience-match score
10. : Compute job-fit score S_{job}
11. : Identify missing or insufficiently represented skills
12. : Generate explanation based on matching factors
13. : End For
14. : Sort jobs by descending S_{job}
15. : Return ranked job list

4) Explainable Job Recommendations

Instead of presenting only a numerical recommendation score, the system generates an explanation describing the factors contributing to the result. The explanation is based on the already calculated semantic and structural scores and the identified skill gaps.

For example, a recommendation may indicate that the candidate has strong alignment with the required programming skills and educational qualifications but has limited representation of a particular cloud or deployment technology.

This provides candidates with actionable information rather than treating the recommendation as an unexplained prediction.

E. Privacy, Transparency, and Reliability Considerations

The system processes resumes and interview responses that may contain personally identifiable information. Therefore, document processing and AI inference are separated into distinct stages. Where cloud-based AI services are proposed, only the information required for the corresponding analysis is passed to the AI processing layer. A local inference configuration using Ollama and local embedding models provides an alternative for privacy-sensitive processing.

The system also maintains a distinction between *deterministic results and AI-generated interpretations*. Numerical calculations such as keyword matching, semantic similarity, response duration, word count, and scoring formulas are computed programmatically. LLMs are primarily used for natural-language understanding, content generation, qualitative evaluation, and personalized explanations.

For interview preparation, question provenance is retained so that historical questions and AI-generated questions are not presented as equivalent sources. Similarly, when a skill is not detected in a resume, the system reports it as "not detected" rather than concluding that the candidate does not possess the skill.

These design considerations improve the interpretability, transparency, and reliability of the proposed CareerNova.

VI. SYSTEM ARCHITECTURE

The proposed CareerNova is designed as a proposed integrated, modular architecture that supports the complete career-preparation lifecycle of a candidate. The system consists of four major modules: *AI Resume Maker, AI ATS Score Checker and Resume Improvement, AI Interview Preparation, and AI-Based Job Recommendation*. A centralized candidate profile acts as the primary data source, allowing information generated in one module to be reused by subsequent modules.

The system begins with user registration and authentication, followed by resume creation or upload. The generated or uploaded resume is processed and can be evaluated by the ATS module. After obtaining the ATS score and improvement recommendations, the user can modify the resume and perform the analysis again. The optimized candidate profile is then utilized by the Interview Preparation module and the Job Recommendation module.

A. User Authentication and Candidate Profile

After registration and login, the user accesses the career-assistance dashboard and provides the information required for resume creation. Candidate information such as education, skills, projects, certifications, internships, achievements, and experience are maintained as part of the candidate profile.

The candidate profile and resume information provide the common data source for the subsequent modules. This enables the system to reuse previously entered or extracted information instead of requiring the candidate to repeatedly provide the same details.

B. AI Resume Maker

The AI Resume Maker allows the user to create a professional resume by entering the required candidate information and selecting an appropriate resume template. The system processes the provided information and generates the resume according to the selected template.

The generated resume can be previewed, edited, saved, and downloaded by the user. The saved resume can subsequently be directly utilized by the ATS module, while an alternative resume can also be uploaded if required.

C. AI ATS Score Checker and Resume Improvement

The ATS module accepts either the resume generated by the Resume Maker or a newly uploaded resume. The uploaded document is processed using document-extraction techniques. PDF and DOCX files can be processed using PyMuPDF and python-docx, while Tesseract OCR can be proposed for scanned documents.

The extracted resume information is analyzed using rule-based checks, NLP processing, keyword matching, and semantic analysis. The system evaluates resume structure and content and generates an ATS-oriented score. When a target job description is available, semantic embeddings are used to compare resume and job requirements. The proposed technology stack uses BAAI/bge-small-en-v1.5 embeddings with pgvector for vector-based similarity operations.

Based on the analysis, the system identifies weaknesses such as missing skills or keywords, grammar issues, readability problems, weak descriptions, and other resume-quality issues. AI-generated recommendations are provided to the user for improvement.

This allows the candidate to verify whether the modified resume achieves improved ATS compatibility.

D. AI Interview Preparation

The AI Interview Preparation module uses the candidate's resume and profile to generate personalized interview preparation.

The module provides two pathways based on the candidate's career stage.

- *On-Campus/Fresher:*

The system extracts relevant information from the candidate's resume, including skills, education, projects, internships, and other available information. This information is proposed to generate questions relevant to fresher and campus-placement preparation, with company-specific information where available.

- *Off-Campus/Experienced:*

The proposed framework incorporates the candidate's resume together with the job description, company information, and experience - related information to generate questions specific to the target role and organization.

After the required information is processed, the generated questions are provided through two preparation modes: Prep Test and Test Myself.

E. Prep Test and Test Myself

The Prep Test mode provides text-based interview questions along with solutions or expected answers, allowing users to study and prepare before attempting an interview.

The Test Myself mode provides an interactive audio/video mock-interview experience. The system presents questions to the candidate, records the responses, and evaluates the candidate's performance. Audio responses can be converted into text using Whisper-based speech recognition before further analysis. The proposed technology stack supports Groq Whisper and faster-whisper for speech-to-text processing.

The evaluation considers multiple aspects of interview performance, including technical response quality, completeness, communication, grammar, fluency, filler words, repetition, response duration, and confidence-related indicators. Video-based analysis can additionally examine observable facial, posture, and gesture-related characteristics.

The system generates scores, identifies mistakes, and provides personalized feedback and improvement recommendations. Measurable properties such as response duration, word count, filler words, repeated words, and words-per-minute can be calculated programmatically, while AI models can be used for semantic response evaluation and natural-language feedback.

F. AI-Based Job Recommendation

The Job Recommendation module uses the candidate's resume and profile together with the filters specified by the user to identify relevant employment opportunities. Candidate attributes such as skills, education, experience, projects, and qualifications are compared with available job requirements.

Semantic embeddings and structured matching are used to determine the relevance between the candidate profile and job requirements. The system subsequently ranks suitable opportunities and presents personalized job recommendations.

The proposed architecture initially supports user-provided job descriptions, while legitimate job APIs or feeds can be integrated for obtaining job listings.

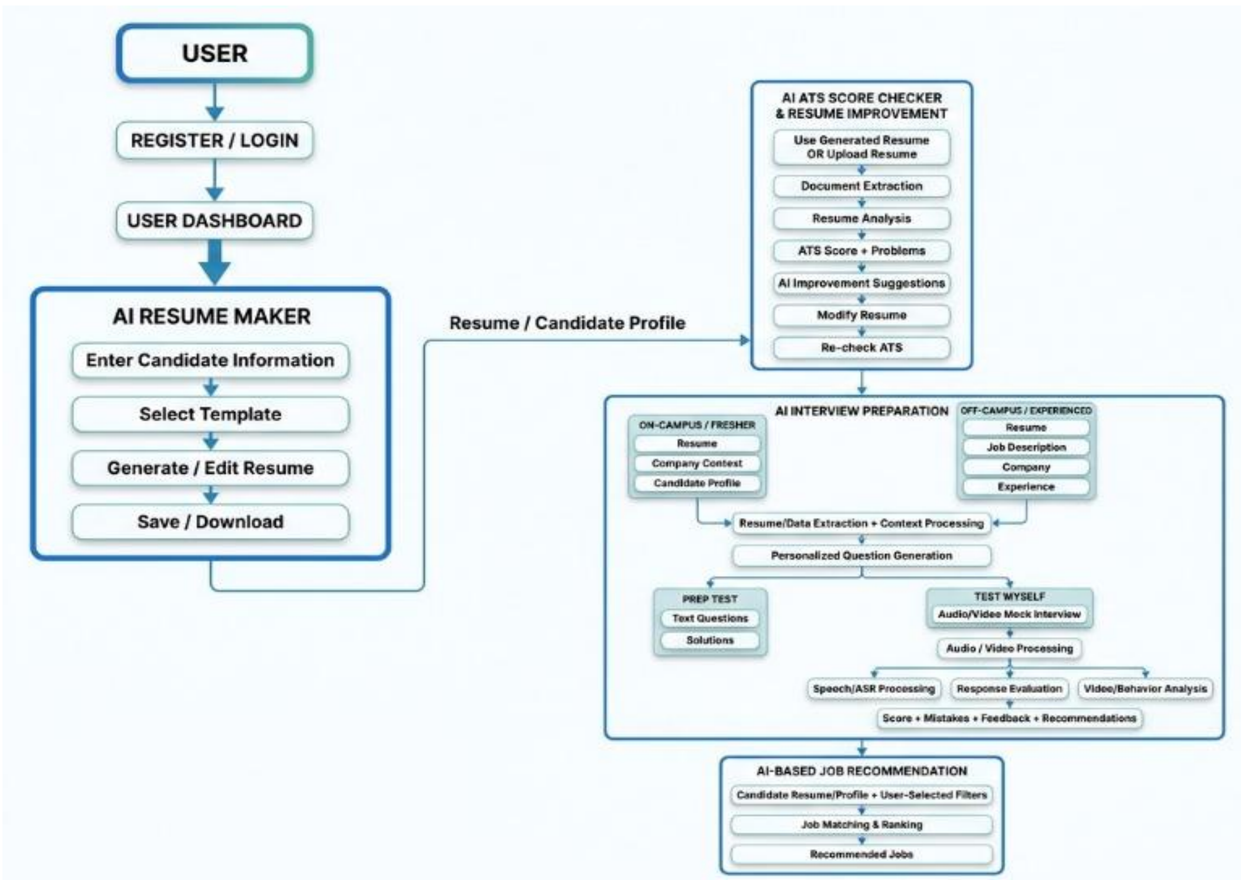

Fig 1. *System Flow Diagram*

VII. TECHNOLOGY STACK

The frontend communicates with the *FastAPI* backend through RESTful APIs. The backend manages authentication, document processing, database operations, and AI-related tasks. *PostgreSQL with pgvector* provides both structured data storage and vector similarity operations.

Resume documents are processed using PyMuPDF, python-docx, and Tesseract where required, while semantic analysis uses sentence-transformers and the BAAI/bge-small-en-v1.5 embedding model. Large language model services are used for semantic interpretation, content generation, and interview evaluation, while Whisper-based models process audio responses.

Background processing with Redis and worker services prevents computationally intensive operations from blocking regular API requests.

Layer	Technology
Frontend	Next.js (App Router), TypeScript, Tailwind CSS
UI Components	shadcn/ui, Lucide
Backend	Python 3.12, FastAPI
Authentication	JWT
Database	PostgreSQL 16
Vector Database	pgvector
Document Processing	PyMuPDF, python-docx
OCR	Tesseract
NLP	spaCy
Embeddings	BAAI/bge-small-en-v1.5, sentence-transformers
Primary LLM	Google Gemini Flash
Secondary LLM	Groq with Llama
Local LLM	Ollama
Speech-to-Text	Groq Whisper, faster-whisper
Background Processing	Redis + Worker
File Storage	Local /uploads storage
Containerization	Docker Compose

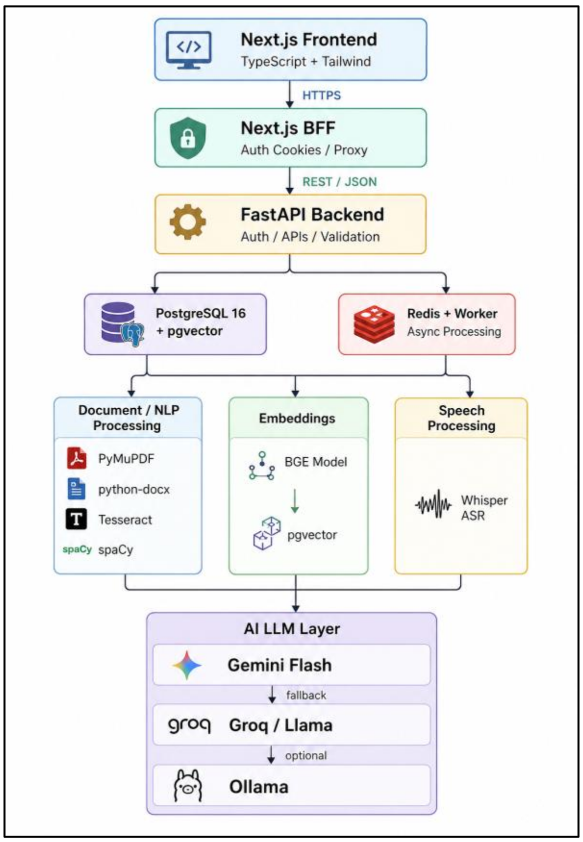

Fig 2. *Technology Stack*

VIII. DISCUSSIONS AND ILLUSTRATIVE SCENARIOS

CareerNova can be implemented and evaluated across its four modules:

1. AI Resume Maker:

a) Successfully generated professional resumes from user-provided information.

b) AI-assisted content generation improved clarity and structure, producing concise professional summaries, project descriptions, and experience narratives.

c) Template selection and live preview simplified formatting. Sample resumes demonstrated consistent organization and professional presentation.

Fig 3. *AI Resume maker workflow*

2. AI ATS Score Checker & Resume Improvement:

a) Experimental evaluation showed measurable improvements in resume-job alignment.

b) Example results:

1) Fresher resume for Python Developer: Initial score 52%, improved to 78% after adding missing Python/Pandas keywords.

2) Student resume for Data Analyst: Initial score 61%, improved to 84% after SQL keyword enhancement.

3) Developer resume for Software Engineer: Initial score 70%, improved to 86% after strengthening project descriptions.

c) The system provided actionable feedback on missing skills, weak bullet points, grammar, readability, and ATS-related improvements.

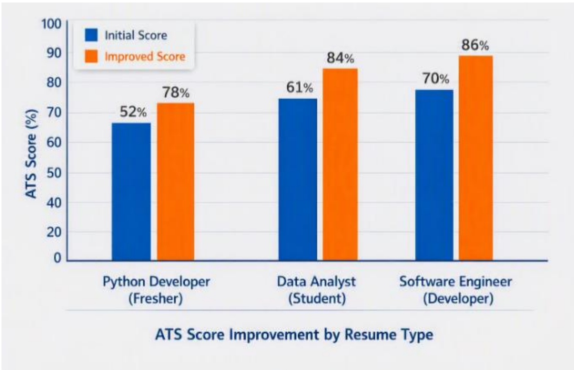

Fig 4. *Illustrative ATS-oriented resume analysis and improvement work flow*

3. AI Interview Preparation:

a) Generated personalized interview questions based on resumes and job descriptions.
b) Mock interviews with speech-to-text analysis provided feedback on relevance, completeness, fluency, and technical accuracy.
c) Adaptive follow-up questions made practice sessions realistic and interactive.
d) Candidates received structured feedback highlighting correct points, missing concepts, and improvement areas.

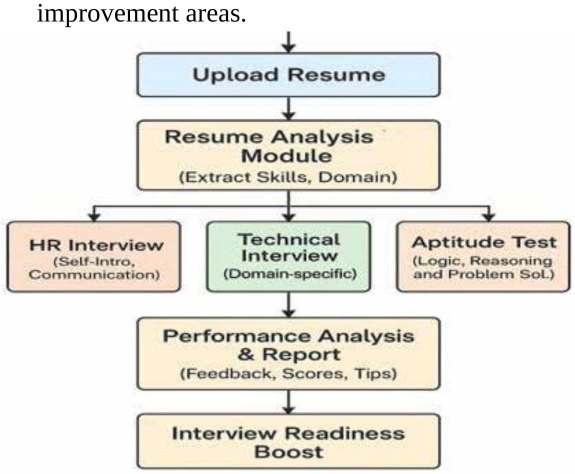

Fig 5. *Conceptual mock-up of the proposed personalized interview module*

4. AI-Based Job Recommendation:

a) The proposed module is designed to calculate job-fit scores by combining semantic embeddings with rule-based subscores for skills, experience, education, and keywords.
b) Explanations were generated using LLMs, ensuring transparency.
c) Hypothetical walkthroughs demonstrated clear outputs such as: *"Your overall fit is 78%, driven mainly by strong skills and education match; adding Docker and AWS experience would raise your score further."*

Fig 6. *Illustrative output of the proposed job recommendation module.*

Overall, the proposed framework is intended to provide a proposed integrated and explainable approach to career preparation. By connecting resume generation, ATS-oriented analysis, interview preparation, and job recommendation through a shared candidate profile, CareerNova is designed to reduce information repetition and support personalized guidance across multiple stages of the career-development process. The practical effectiveness of the proposed framework requires validation through future prototype implementation and empirical evaluation.

IX. LIMITATIONS

Although the proposed framework integrates resume creation, ATS-oriented analysis, personalized interview preparation, and job recommendation, several limitations and research challenges should be considered during future implementation and evaluation:

- *User Information:*

Incomplete, incorrect, or outdated information may affect the quality of generated resumes, analysis, and recommendations.

- *AI-Generated Content:*

AI-generated descriptions and suggestions may not always accurately represent the user's intended meaning and require user verification.

- *Document Extraction:*

Complex layouts, tables, images, columns, scanned documents, or unusual formatting may affect resume text extraction and analysis.

- *Resume Design:*

Visual customization is limited to the templates and design options implemented in the system.

- *ATS Score Variability:*

ATS technologies differ across organizations and recruitment platforms; therefore, the generated score may differ from commercial ATS scores and cannot fully represent candidate suitability.

- *Semantic and NLP Analysis:*

Matching accuracy depends on embedding quality and the completeness of resume and job-description text. Synonyms, abbreviations, and contextual information may not always be correctly identified.

- *AI and API Dependency:*

LLM and ASR services may be affected by availability, latency, API limits, network connectivity, response quality, and operational cost.

- *Interview Speech Analysis:*

Accents, pronunciation, background noise, and recording quality may affect speech recognition and subsequent response analysis.

- *AI Interview Evaluation:*

AI-based scoring may not fully represent human expert judgment, while speech characteristics cannot directly measure attributes such as confidence or honesty.

- *Potential Bias and Language Support:*

Language and speech models may perform differently across accents and communication styles, while the current system primarily targets English-language interviews.

- *Job Recommendation:*

Recommendation accuracy depends on the quality of resume and job-description information. The general-purpose embedding model is not fine-tuned for resume–job matching and may underperform specialized models [5].

- *Human Verification:*

AI-generated resume content, ATS scores, interview evaluations, and job recommendations should be reviewed and interpreted by users before being used for career-related decisions.

X. FUTURE SCOPE

The proposed CareerNova framework provides several directions for future implementation, validation, and enhancement:

- *Advanced Resume Customization:*

Add professional templates, themes, layouts, additional formats, and job-description-based customization of resume content, skills, projects, and keywords.

- *Enhanced ATS and Semantic Analysis:*

Incorporate advanced transformer-based models, semantic embeddings, industry-specific ATS analysis, and explainable scoring for more accurate resume-job matching.

- *Skill-Gap and Career Guidance:*

Identify missing skills required for target jobs and provide personalized, learning-oriented recommendations for skills, projects, and resume improvement.

- *Multilingual Support:*

Extend resume analysis, job-description processing, and interview preparation to Hindi, regional languages, and other multilingual content.

- *Real-Time AI Assistance:*

Provide recommendations while users create or edit resumes and improve the quality of contextual suggestions using advanced and accessible AI models.

- *Job Portal and Knowledge Graph Integration:*

Integrate suitable job platforms and Knowledge Graph-based reasoning to connect roles, skills, certifications, and industries for improved job recommendations.

- *Advanced Interview Evaluation:*
Add a proposed integrated coding environment with automated code evaluation, improved multimodal interview analysis, and more reliable audiovisual assessment.

- *Human-AI Hybrid Feedback:*
Introduce human mentors or instructors into the feedback loop to complement AI-generated recommendations and improve their reliability.

- *Advanced Recommendation Models:*
Upgrade the job-matching engine using cross-encoder and trained ensemble-classifier approaches when sufficient labeled interaction data becomes available, with adaptive feedback for continuous improvement.

XI. CONCLUSION

This paper presents CareerNova, a proposed integrated AI-powered career-assistance framework comprising four interconnected modules: AI Resume Maker, AI ATS Score Checker and Resume Improvement, AI Interview Preparation, and AI-Based Job Recommendation. The proposed framework combines artificial intelligence, natural language processing, semantic analysis, structured information extraction, and explainable recommendation techniques to support multiple stages of career preparation.

The proposed AI Resume Maker is designed to combine structured candidate information, AI-assisted content generation, and template-based document creation to support the preparation of professionally organized resumes. The proposed ATS-oriented analysis module combines deterministic evaluation, keyword and skill matching, and semantic similarity to analyze resume-job alignment and generate actionable improvement recommendations.
The proposed Interview Preparation module uses candidate information, company or campus context, and job-description analysis to generate personalized practice questions and support interactive mock interviews. The proposed framework is designed to provide structured feedback related to relevance, completeness, technical coverage, fluency, repetition, and answer structure while recognizing that AI-based evaluation cannot fully replace human judgment.
The proposed Job Recommendation module combines sentence embeddings, deterministic matching, and explainable feedback to identify potentially relevant employment opportunities and highlight skills that are not sufficiently represented in the candidate profile.
The main contribution of CareerNova is the integration of multiple career-support functions within a unified framework supported by a shared candidate profile. Rather than requiring users to repeatedly provide the same information across independent platforms, the proposed architecture is intended to enable information reuse and personalized guidance across resume preparation, ATS-oriented analysis, interview practice, and job recommendation.
As the framework is currently research-based and has not yet been implemented as a complete operational system, future work should focus on prototype development, empirical testing, user studies, benchmark datasets, and comparative evaluation. Future enhancements may include multilingual support, advanced recommendation models, coding-interview evaluation, multimodal interview analysis, and integration with legitimate job-data sources.

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