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Aurora AI – An AI-Powered Career Optimization Tool

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Abstract--An AI-powered career optimization tool called Aurora AI gives job seekers real-time, useful insights into their LinkedIn profiles and resumes while putting privacy first.In order to ensure that personal data never leaves the user's device, it was designed as a browser-based Single Page Application (SPA) with 100% client-side processing. The system uses the Google Gemini API to offer quantitative scoring (Resume Fit Score, ATS Compatibility, Profile Completeness), customised improvement recommendations that align with specific job descriptions, and keyword gap analysis. A context-aware AI chat assistant enables interactive, follow-up guidance based on the most recent analysis results. Through serverless architecture and secure API key handling, Aurora AI prioritises security while offering a visually appealing Aurora-themed user interface, accessibility compliance, and responsive design. The only resume formats supported at the moment are PDFs and manual LinkedIn input. Keywords: Prompt Engineering, Gemini API, Ameena AI, Intelligent Tutoring Systems, Personalised Learning, Multimodal Learning, Self-Regulated Learning, Artificial Intelligence in Education, and React SPA. In the future, browser extensions, user accounts, and compatibility with.docx will be added. Aurora AI fills the gap between individualised, privacy-preserving career counselling and generic applicant tracking systems.

Keywords:- Career Optimisation Driven by AI, Privacy-Preserving Resume Analysis, Client-Side Processing, Compatibility with Applicant Tracking Systems (ATS), and Context-Aware Conversational Assistant

I. INTRODUCTION

In today's fiercely competitive job market, employers mainly rely on Applicant Tracking Systems (ATS) to screen applicants before a human recruiter ever sees their resume. Studies show that more than 75% of resumes are automatically rejected by ATS filters because they don't match job descriptions, have formatting errors, or lack keywords. The majority of career optimisation tools available today focus on LinkedIn profiles or resumes, provide only generic feedback, or rely on server-based processing that compromises data privacy..

This makes a unified, intelligent, and privacy-preserving solution that provides job seekers with actionable, data-driven advice imperative. Aurora AI has created a browser-based, next-generation Single Page Application (SPA) that handles user data solely on the client side in order to get around this problem. By using the Google Gemini API to provide quantitative scoring, keyword gap analysis, and personalised improvement recommendations, it assists users in optimising their LinkedIn profiles and resumes for maximum impact on the job market. One unique feature of Aurora AI is its context-aware conversational assistant, which enables interactive, customised advice based on the results of the most recent analysis. The system focuses on security and privacy by using a serverless setup and handling API keys securely. This approach ensures that the private data of resumes remains within the user's browser. Aurora AI offers a frictionless workflow complemented by an engaging user experience; its space-age interface is titled Aurora, hotkeys for getting around, semantic HTML, and ARIA attributes for screen readers, plus a fully responsive design. It combines deep AI capabilities with rich data and client-side processing. Aurora AI serves professionals, independent contractors, and job seekers with a scalable solution for today's labor market. It combines general ATS optimization tools with personalized career coaching. Standard ATS keyword checkers and thorough, personalized career coaching are kept apart by Aurora AI. Current resume data stays in the user's browser. Platforms by integrating AI-driven document analysis and privacy-focused design, and designing an immersive user experience. A major advancement at the nexus of AI, privacy, and digital career development, this work shows that client-side AI solutions can provide safe, scalable, and highly actionable career guidance.

Aurora AI also gives accessibility and user experience (UX) top priority. It uses semantic HTML5, ARIA attributes, and a responsive three-column layout to ensure usability on all devices and for users who rely on assistive technologies. The lightweight, bundler-free architecture uses import maps and ES Modules to optimize deployment and boost performance, but it heavily relies on browser caching for faster repeat usage. Aurora AI was created to solve these issues by implementing a client-side, privacy- first method of career optimisation. I see. Because Aurora AI is a browser-based Single Page Application (SPA), all sensitive data, including resumes, LinkedIn profiles, and job descriptions, is analyzed directly in the user's browser thanks to its 100% client-side processing.

II. LITERATURE SURVEY

When Bhatia et al. (2019) [1] implemented an end-to-end resume parsing and candidate ranking system using BERT, they achieved strong results on parsing benchmarks and job-fit assessments. Their work demonstrated the value of contextual embeddings for hiring applications and set a standard for automated resume-job matching. Nevertheless, the system lacked LinkedIn integration and multi-source analysis, and it only accepted text resumes. Furthermore, the lack of interactive feedback and visualization made it less user-centric. As a result, it kept putting parsing accuracy ahead of giving job seekers helpful guidance. Zhang et al. (2017) proposed Resume Vis, a visual analytics system that extracts insights from resumes using text mining and semantic analysis. [2] The tool enabled users to examine skill distributions and career paths through interactive visualizations. While it was effective for data exploration, it lacked real-time personalization and job description benchmarking and was only helpful for visualization. Furthermore, the system provided no recommendations for enhancing resumes or optimizing keywords. As a result, Resume Vis served more as an exploratory tool than as a full career optimization solution. Resume Flow, an automated framework for creating unique job-specific resumes using large language models like Gemini and GPT-4, was proposed by Zinjad et al. (2024) [3]. Based on prompt-driven LLM outputs, the method showed great promise for improving resumes and customizing content. However, very little diagnostic feedback was provided with the system that had a generation-oriented approach rather than an evaluation-based approach. Further, it was server-dependent due to lack of offline or client-side processing, which raises privacy concerns. Hence, Resume Flow improved customization without security, transparency, or guiding the user iteratively. Career Mapper is an automated system developed by Lai et al. (2016) [4] which evaluates one's LinkedIn profiles through extensive online data analysis. This tool provides users with recommendations as to how they can improve their professional presence in front of a LinkedIn audience. Its functionality is, however, confined to LinkedIn profiles only and also does not support any job-specific benchmarking or ATS-focused resume analysis. Moreover, it is not comprehensive owing to the absence of integrated resume optimization and keyword gap analysis. Therefore, Career Mapper is good to go for profile evaluation but not essentially a full-suite career optimization solution. Daryani et al. (2020)[5] proposed an Intelligent Resume Matching System that matches resumes to job descriptions using TF-IDF and multiple machine learning algorithms. The system ranks candidate suitability with ranking models and natural language processing techniques. It displays great results in instances of simple job profiles but poorly for jobs which are intricate or nuanced in their description. Furthermore, this framework has a very poor user interface and user experience; it provides little personalization, thereby making the interaction awkward to use and thus deterring its wider adoptionA resume-job matching method which uses SpaCy-based NER and semantic scoring to enhance candidate evaluation is presented in the study "Improved Candidate Matching using Semantic Analysis", ASTESJ, 2021[6]. This system provides a high accuracy with an F1 score of approximately 91% and proves that the semantic-driven analysis has become a useful tool for enhancing the quality of matches. The framework, though yielding good results, does not allow for much user interaction because of the lack of visualization tools and an interactive assistant.

Moreover, the approach hardly scales for dynamic platforms like LinkedIn and therefore could hardly be deployed in cases involving real-time hiring. Anand and Giri, 2023[7] proposed the use of large language models (LLMs) for keyword. Apart from analysis, this also involves ATS-aware formatting to optimize resume design for ATS.

According to the research, LLMs can significantly enhance resumes' ATS compatibility, raising the chances of their successful parsing and ranking.

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However, since the method is focused on ATS optimization and lacks multimodal career support, such as LinkedIn integration or interactive chat support, its general applicability in modern recruitment ecosystems remains low. The Resume2Vec framework introduces an intelligent resume embedding method for candidate ranking within applicant tracking systems, MDPI Electronics, 2023[8]. Unlike typical keyword-based methods, this research relies on vectorized resume representations and builds a deep NLP parsing pipeline to enable more refined matching. While this method holds great promise of improving ATS ranking of candidates, it depends on complex embeddings that require high processing power. Furthermore, since personalization features are not included in this framework, and regional privacy concerns have not been addressed, its application in sensitive or user-specific recruitment situations may be severely restricted. With the purpose of semantic ranking of candidates against job descriptions, Vanetik & Vanetik, 2022[9] presented a resume-job matching framework in which character n-grams were combined with representation based on embedding. In comparison with typical keyword-based techniques, the proposed technique raised the accuracy of resume ranking, which serves as evidence of how well embeddings capture semantic similarity. From the perspective of a candidate seeking resume feedback, the system's usability is limited due to the omission of personal improvement suggestions and user interaction. ResearchGate's Intelligent Resume Tracking System (Omanakuttan et al., 2024)[10] combines NLP and ML parsing with automated keyword extraction and ranking. centered on HR rather than applicants. simplifies recruiter screening by implementing automated ranking. does not provide suggestions that empower job seekers. Rahman et al. (2024[11]) presented an Intelligent Resume Screening Tool that combines a hybrid natural language processing (NLP) and rule-based methodology with AI-driven suggestions for blog and LinkedIn profiles. To assist candidates in enhancing their profiles, the system offers content analysis and basic AI advice. Although good at providing automated recommendations, its practical usefulness for dynamic career guidance is limited because it only provides surface-level recommendations and lacks context awareness, personalisation, and real-time feedback. A general review of resume parsing systems and the application of semantic search to match applicants with job requirements can be found in the Wikipedia overview on Resume Parsing and Semantic Search (2022)[12]. It provides a deep understanding of the state of the art, challenges, and theoretical backgrounds of resume analysis. However, it is not very useful for empirical research or system development due to the fact that it is not an experimental source and lacks concrete evaluation, interactivity, and practical insights on the implementation. The ethical aspects of AI-based hiring are discussed, like bias, transparency, and fairness, in detail in the Wikipedia article Artificial Intelligence in Hiring 2025[13].

The paper does not contribute any algorithmic techniques, experimental results, or technical solutions and therefore is limited to theoretical and ethical discussion rather than the actual development of a system, despite successfully pointing out the potential risks and societal implications of using AI in hiring. ReZoom.io guide 2023[14] on Fine-Tuning Resume Keywords for ATS presented a very useful summary of techniques for resume optimisation for applicant tracking systems, including synonym usages and keyword phrasing. Although the guide provides practical advice for job seekers, its applicability in academic or experimental settings is limited due to its lack of empirical evaluation, informal nature, lack of research foundation, and lack of peer review. The Smart Resume Analyser introduced by Bhor et al. in 2023 uses RNN-based NLP techniques to extract keywords from resumes. However, the limited scope of the approach-it was only tested on a s mall dataset and does not support dynamic platforms like Linke dIn-restricts the wider applicability of the model in real-world recruitment scenarios. As an example, many AI-based approaches have been used to enhance resume evaluation and job matching, including natural language processing (NLP), machine learning, and deep learning, as seen in the literature of both automated resume analysis and personalised resume generation. While rule-based and keyword extraction technologies offer simple filtering, deep learning models like RNNs and LLMs have achieved advanced capabilities in identifying candidate skills and predicting their suitability for particular jobs. In general, despite all the progress, further research is needed toward the goal of developing complete, scalable, and very accurate résumé analytic systems able to handle real hiring situations.

III. METHODOLOGY

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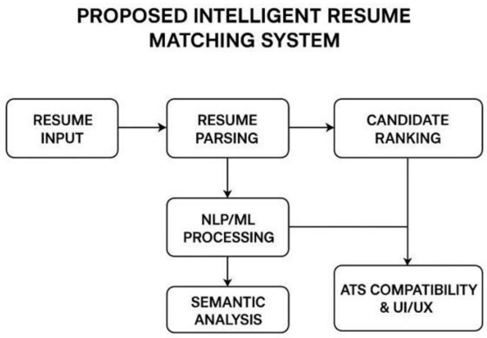

The block diagram illustrates the architecture of the proposed intelligent resume matching system that is designed to streamline and automate the candidate evaluation process. First comes resume input, at which stage candidate resumes are collected in different formats. The resumes are then subjected to a process called Resume Parsing, which extracts structured data such as work history, education, skills, and personal information. After parsing, the data then undergoes NLP/ML Processing with machine learning and natural language processing methods that look into textual content for important patterns and extract semantic information. Further, the Semantic Analysis module enhances understanding even further and provides the ability to match experiences and skills against job requirements more accurately by assessing their contextual meaning. Simultaneously, the Candidate Ranking system assesses and rates each applicant based on experience, skill alignment, and relevance.

Having ensured ATS Compatibility & UI/UX, the system fine-tunes the output to make it compatible with applicant tracking systems and shows the results in an easy-to-use interface. On the whole, this architecture could further enhance the efficiency of hiring by enabling automatic, accurate, and fast resume screening. The proposed intelligent Aurura AI, with the use of state-of-the-art NLP and ML techniques, is designed for effective assessment, ranking, and matching of applicant resumes with the requirements of the job. The following elements make up the system's block diagram: Resume Input: In this initial stage, the system accepts resumes from individuals seeking employment. Resumes can be submitted in various formats such as TXT, DOCX, and PDF, which the system ingests for the next stage. Resume Parsing: Once the resume is submitted, this parsing module translates unstructured text from the resume into structured information. The parsing identifies important fields and structures the resume into a machine-readable format, with fields including personal information, education, employment history, skills, and certifications. This step functions to lead to accurate processing later in the flow. NLP/ML Processing: After parsing, NLP and ML algorithms can utilize the structured data. While ML models identify patterns, skills, and experience that are matched to specific job requirements, natural language processing or NLP techniques extract meaning and context from the text.. This module creates intelligence for the system through an analysis of the content of the resume. Semantic Analysis: This module performs deep semantic understanding of job-related keywords, candidate qualification, and context similarity. It ensures that the qualifications and experiences of candidates align with the description of the vacancy in a meaningful manner, and not just because of keyword matching. Candidate Ranking: Based on the insight obtained from NLP/ML processing and semantic analysis, the system ranks candidates for suitability for the post. Many factors are considered during ranking, including education, experience relevance, skill match, etc. ATS Compatibility & UI/UX: And lastly, the system ensures that the resumes it processes are compatible with the Applicant Tracking Systems or ATS, which are used nowadays by businesses for the automated filtering of resumes. The design of UI and UX is taken into consideration to present the recruiters with clear and useful information. Front-end libraries: PDFOne of the finest browser-based libraries to parse and extract text from PDFs is js-dist. The famous and versatile charting library Chart.js renders the interactive and aesthetic doughnut charts for scoring. html2pdf.js: It is a utility library that combines html2canvas & jsPDF to let client-side creation of PDF reports directly from the HTML content of the application. HTML5: The modern semantic markup for application structure. CSS3: A handcrafted, from-scratch stylesheet that uses Flexbox and Grid extensively for layout, CSS Custom Properties or Variables for theming, and other advanced features such as backdrop-filter that creates the glassmorphism effect and @keyframes for animations. Bootstrap 5.3: Used sparingly, mostly for its robust grid system (row, col-md-6) and a few utility classes to expedite development. The rich icon set utilised throughout the application is provided by Font Awesome 6.Google Fonts: Because of its crisp, easily readable font, the 'Inter' font is used. Construct and Environment: Import Maps & ES Modules (ESM): The project employs a contemporary,

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bundler-free methodology. The development setup is made simpler by the <script type="import map"> tag in index.html, which enables the browser to resolve package names (such as @google/genai) to their CDN URLs directly. Dynamic DOM Manipulation: The entire analysis results page is created.

IV. RESULT

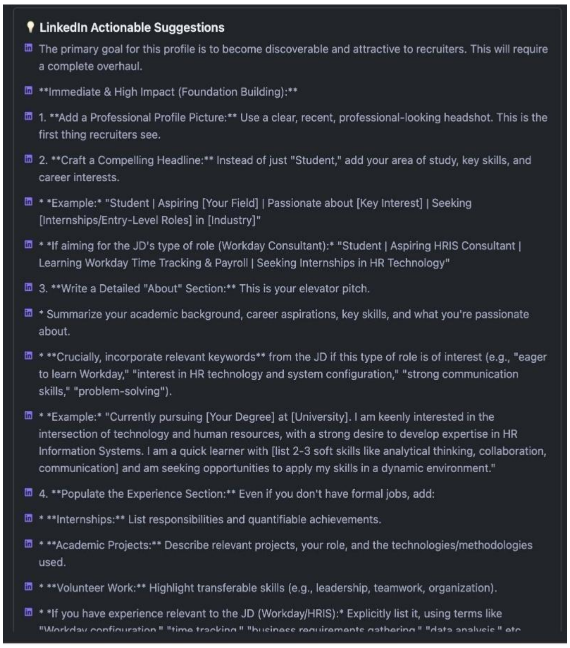

Fig 4.1 - LinkedIn profile improvement tips.

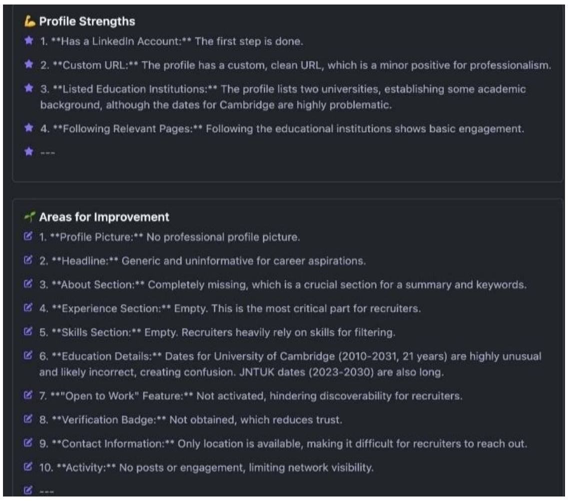

Fig 4.2 - LinkedIn profile improvement.

Fig 4.3 - Missing job-related keywords.

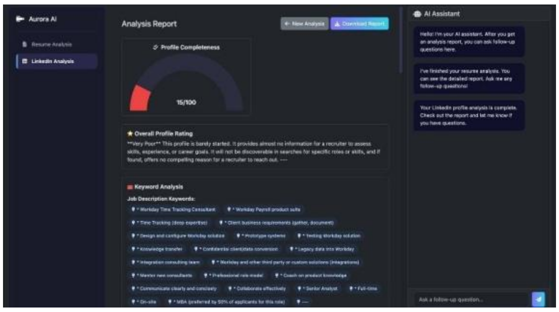

Fig 4.4 - “LinkedIn profile analysis dashboard.”

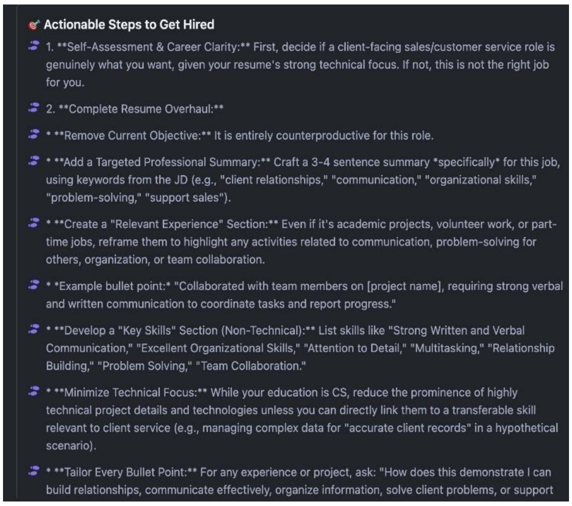

Fig 4.5 - “Improve resume to get-hired”

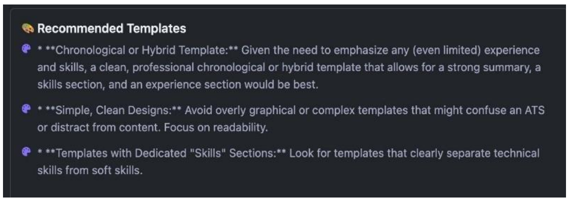

Fig 4.6 - “Use clean simple template.”

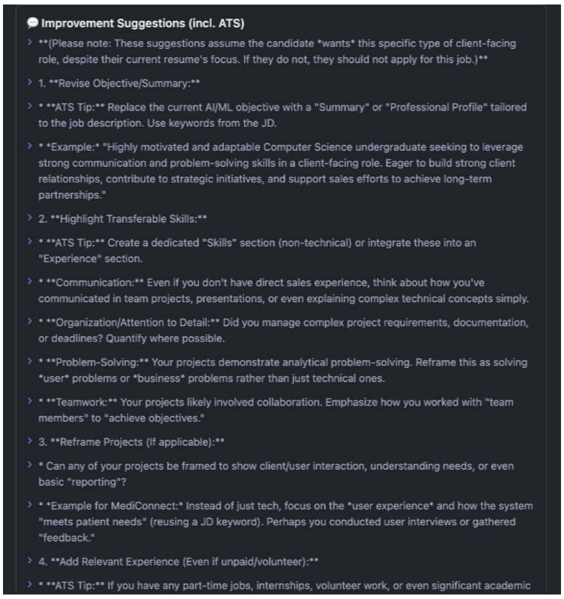

Fig 4.7 - "Improve resume for job"

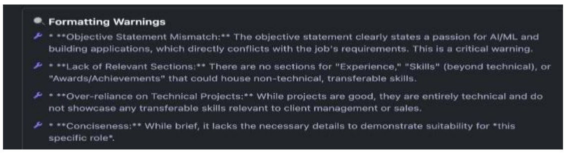

Fig 4.8 - "Resume doesn't match role."

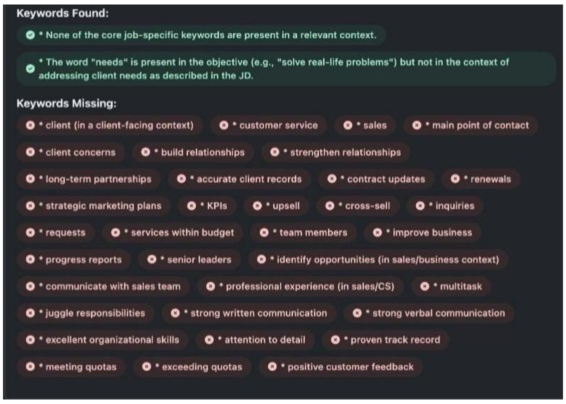

Fig 4.9 - "Missing important job keywords"

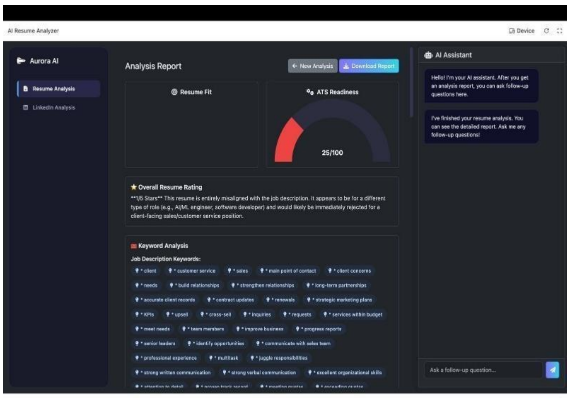

Fig 4.10 - "Resume score is low."

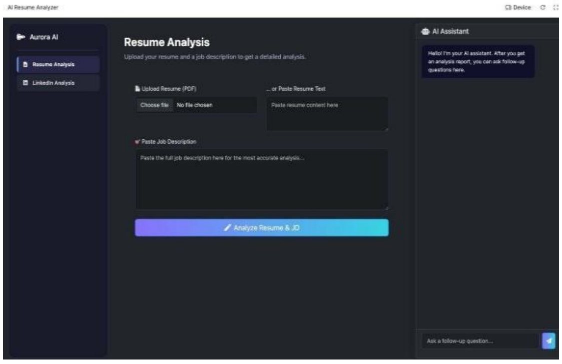

Fig 4.11 – "Tool for resume analysis"

The Aurora AI Resume Analyser was used to assess how well a candidate's resume fitted into the job description of a customer service or sales position with direct interactions with clients. The ATS Readiness Score, as calculated by the analysis, was 25 out of 100, indicating an extremely low coherence with the job description. The general rating for the resume was 1 Star out of 5, indicating a huge mismatch in the skills attributed to the professional role being applied for. Instead, this resume seemed focused on purely technical positions such as software development or AI/ML engineering. Further, the format warnings raised several important issues-for instance, the objective statement put strong emphasis on AI/ML applications, which goes against the emphasis on the need for interpersonal and communication skills in the target job description. In addition, there were no specific sections for nontechnical, transferable skills or accomplishments which would stand to gain the candidate the opportunities of teamwork or problem-solving. According to the keyword analysis, the resume did not reveal any of the primary job-specific keywords in a relevant context. In fact, several of those keywords related to "client," "customer service," "sales," "building relationships," and "strong written/verbal communication" were not at all mentioned. Furthermore, even though the word "needs" was used, it did not reflect the emphasis required by the client needs that are called for in the job description. This analysis pinpoints the critical gap between the needs of a client-facing position and the highly technical resume. The overdependence on technical projects, without rewording them in either a business or user-centered context, did not convey transferable skills such as effective communication, attention to detail, and problem-solving in a non-technical environment. Poorly structured formatting and no clear skills section further hinder readability and ATS compatibility. More importantly, the

Aurora AI tool provided a critical warning because of the extreme difference between the resume's objective and the job requirements. This indicates that an applicant should consider changing their objective or summary with deep consideration of appropriate keywords from the job description. Without key, job-specific terminology, the resume would most likely fail automated applicant tracking systems and would not impress a recruiter through manual screening. The results reveal that technical skills cannot solely help one get a job that involves managing and dealing with clients and interpersonal relationships. It requires a combination of technical and soft skills with adequate keyword usage and neat formatting to pass both ATS and recruiter evaluation. As such, Aurora AI will work properly because several benefits are associated with resume optimization and analysis, specifically for improving job application outcomes. It guides users on what they need to make critical changes in order to meet standards within their respective industry. This will be accomplished by giving an in-depth ATS Readiness Score and specifying certain formatting issues.

Aurora AI also assists in alleviating a major problem seen when applying for non-technical fields, which is an overemphasis on technical skills. In assisting users to scaffold experiences and projects in a business or user-inspired perspective, the re-framing helps to highlight transferable skills. This aids the overall readability of the resume for both a human recruiter and the applicant tracking system with regards to the structure of the resume and job descriptions. Ultimately, it assists job-seekers in becoming more of an active agent by giving them data-driven insights about their resume, providing strategic self-analysis, and fostering intentional clarity in the career. Aurora AI is effective in addressing employability issues for individuals living in highly competitive labour markets where automated systems are the process used to filter candidates.

V. CONCLUSION

As automated Applicant Tracking Systems ATS increase, its input is still high-level, limiting helpful suggestions for specific improvements. The most helpful features of Aurora AI reside in a preliminary diagnosis of resume weaknesses and alerting candidates to general issues that could be preventing successful ATS screening. These shortcomings thus bring to light the need for more sophisticated solutions that will offer industry-specific templates, adaptive learning, and personalized recommendations which allow candidates to better tailor their resumes. This means there is much room for growth in resume optimization technologies, especially in the area of bridging technical expertise with client-facing and business-oriented positions. Despite such setbacks, Aurora AI is a helpful initial tool that points out common errors and encourages applicants to make more purposeful edits. Due to its ability to deliver quantifiable ATS compatibility scores, it acts like a helpful benchmark for job seekers. All the same, research makes it crystal clear that immense opportunity for enhancement of the system through the inclusion of machine learning models exists, which will be able to adapt to different industries, personalize suggestions, and learn from the newly updated job descriptions. These would make the tool offer intelligent, role-specific resume enhancements rather than mere generic analysis. While Aurora AI is a good starting point for automated resume optimization, much more innovation is required so as to provide holistic, customized, and functional solutions that optimize the performance of the job seekers in cutthroat markets. Aurora AI Resume Analyzer is quite a helpful tool in judging how a resume fits into a particular job description. It offers a systemized review of ATS preparedness through a numerical score, identification of formatting errors, and keyword research on missing or unnecessary terms. The critical flaws identified quite well by the tool include poorly aligned objectives, a lack of the skills section, and an excessive reliance on technical projects for non-technical job applications. Candidates can use such insights to identify the areas that need improvement on their resumes and motivate specific changes. The system methodology is still primarily static and rule-based, and it lacks the contextual intelligence needed for in-depth, role-specific optimisation.

VI. FUTURE SCOPE

The potential of Aurora AI in the future lies in a huge increase in its capacity to offer more intelligent, tailored, and flexible solutions for resume optimization. Presently, the system is mainly rule-based, and this framework constrains it from offering industry-specific guidance or deep contextual understanding.

By incorporating advanced machine learning and NLP models, Aurora AI was able to understand resumes and job descriptions contextually and provide proposals regarding context-aware rephrasing of objectives, projects, and skills in addition to missing keywords. Future improvements may also involve dynamic role-specific custom tailoring which would allow it to offer customized templates and suggestions tailored to specific industries, like software development, sales, and customer support. It would improve the impact and relevancy of suggestions significantly. Adaptive learning mechanisms would enable Aurora AI to stay in tune with changing industry practices through ongoing improvement in recommendation logic and scoring algorithms based on enormous datasets of resumes, job descriptions, and hiring results. In order to assist candidates in presenting transferable skills to better reflect a non-technical opportunity, the system may also be enhanced to automatically reframe technical projects to better reflect business impact or problem-solving ability. An interactive user interface may offer a more intuitive editing process, with real-time, actionable feedback such as keyword density highlights, section scoring, and an ATS readability preview. Further enhancement of tool capability to identify accomplishments and implicit soft skills from resume content would support applicants to better highlight their organizational, leadership, and communication strengths. Automation of the job-matching process could be achieved through integrating Aurora AI with career platforms, and job portals, to deliver seamless transition experience for the user to move from optimization, to applying. Finally, ethical considerations must be prioritized in future growth, focusing on reducing bias and improving equity across industries, genders, and demographic groups. Together, these will make Aurora AI a comprehensive, intelligent career assistance platform that promotes better employability results in competitive job markets and a better job search experience.

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