Evaluating Transparency in User Profiling to improve clarity for Resume Screening Systems

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Abstract

Adoption of AI-based resume screening systems gained momentum across the recruitment industry, but continuance of black-box algorithmic decision-making undermined user trust and justice perception. In the present study, we design and test, to an extent, a human-centered transparent resume screening model to critique where candidates may permeate clear and actionable feedback about the fate of their applications. Using a prototype web platform built around advanced natural language processing and explainable AI techniques, our system produces individual rejection explanations to enhance user understanding and agency. We perform a structured user study to assess transparent explanation impacts on applicant trust, perceived fairness, and overall experience. Our findings shall show that transparent AI-based explanation benefits user satisfaction and remedies unethical cases against human-centered design where automation of hiring occurs.

Keywords

Resume Screening,Sentence-BERT, Fairness, Decision Transparency, Human-centered AI, Semantic analysis, Recruitment Automation,

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1 Introduction

In an up-to-date hiring environment, manual screening is inconvenient simply because of the sheer number of applications. On the other hand, applicants often lose satisfaction when automated systems do the entire process. The commonplace "we regret to inform you" letters alleging rejection with no explanation are prone to lose trust toward the whole hiring . For example, one survey revealed that seventy percent of candidates who were rejected wanted at least a brief explanation. This almost makes candidates resentful, which goes against the human-centered AI principles of respect and empowerment for users. [16, 17]

AI-based resume screening solutions improve efficiency but create new ones. Researchers have shown how machine learning models inherit historical biases in providing unfair rankings to candidates, generally acting as "black boxes," wherein the rationale behind their decisions cannot be ascertained. In the real world, such a high level of opacity prevalent in hiring algorithms makes trusting an output tremendously difficult for HR and applicants alike. Although they improve scalability and reduce human workload, serious issues arise relating to transparency, fairness, and accountability-these considerations are of paramount importance when there is the high-stakes decision-making domain of employment. [2, 7]

In the spirit of those challenges, this project aims to develop a transparent, explainable, and fairness-aware resume-screening AI system set under the Human-Centered Artificial Intelligence (HCAI) guiding principles.

2 Literature Review

The study begins with a literature review which looks at the changes in the use of artificial intelligence in the hiring field. It follows the journey from basic automated systems to complicated human-like frameworks. The paper then discusses the developments in natural language processing, the key issues of fairness and bias, and the new trend of making AI systems more transparent and understandable.

Using AI in the hiring area has surely changed the way we do resume reading, making it more automated by using the value of efficiency and scalability. Yet, the traditional methods based on static keyword filters and rule-based matching have a rather narrow understanding of the context and cannot help candidates to get meaningful feedback thus bringing along concerns about fairness and transparency in high-stakes recruitment decisions.

Recently, to get more understanding of the context in the resumes and job description, advanced methods took advantage of the BERT or SBERT transformer-based models. Deshmukh and Raut (2024) [6] implemented SBERT to seize the situations of a sentence, like it was considered on the resume and the job description, to prove that the method relevance detection is going to be better. Then they went even deeper and added BERT-based scoring and ranking mechanisms to their research, thus candidate fit through the use of context embeddings became more audible. At the same time, in one of the first machine-learned resume-job matching systems, Lin et al. (2016) [9] used structured feature extraction and ranking functions

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as well.

There have been lots of other studies that work on the ethical part of AI for recruitment. Researches like Mujtaba and Mahapatra (2023) [12] outlined the major fairness metrics and bias removal strategies in recruitment AI and Moreover they highlighted the significance of the disclosure of the model decisions.Similar to our previous statement, an ACM (2023) [3] survey that incorporates a variety of disciplines was done and the issue of algorithmic responsibility, legal aspects, and the social side of the solution were also mentioned. Ghosh et al. (2023) [8] have published a short article where they outline the latest developments of AI in recruitment and thus explainability, implementation of governance, and engaging people in decision-making will be the solution for fair results.

At a hands-on level, various implementation efforts exemplify the application of AI in actual experimental or prototype hiring tools. Vihari et al. (2023) [18] illustrated a BERT-based resume screening system that was dedicated to automating acceptance and rejection decisions along with confidence scores. Baghel et al. (2023) [1] introduced a lightweight AI-driven method to accelerate the screening process at the same time as ensuring the traceability of the results. In a similar vein, Daryania et al. (2023) [4] actualized an NLP-driven similarity engine as a tool to match job descriptions with resumes by relying on feature extraction and cosine similarity. The authors Paranthaman et al. (2023) [13] were concentrating on improving recruitment pipelines by deploying machine learning models that were trained on applicant features specific to the role.

Explainable AI (XAI) is the main point in the increase of the trust level. SHAP and LIME are amongst the most popular methods to clarify the output for complicated models. These methods allow us to understand what characteristics of the problem have played a major role in supporting the result. For instance, the recruitment topic is the context, and the candidate is the one who needs to be informed clearly why he got as answer rejection. Eiband et al. (2018) [7] and Wang et al. (2019) [19] maintain that the quality of the explanation has a direct impact on user trust and the level of system acceptance, mainly, when the latter is presented via end-users' interfaces. Shneiderman (2020) [15] strongly recommends Human-Centered AI as the sole trustworthy paradigm, as it provides the notions of reliability, transparency, and user agency inherent from the initial stages of the project up to the final one.

Large language models have certainly ventured into the recruitment field. Lo et al. (2024) [10] explained a multi-agent resume screening framework that was context-aware and used large language models, enabling the explainability of the decision via the dialog-driven interactions between the agents and the applicants. Lin et al. (2021), while summarizing the influence of AI on recruitment, warned that the implementation of the automatic recruitment process without ensuring ethical protection is dangerous and proposed a mixed-method evaluation where the users' trust, accuracy, and transparency are combined.

All together, these studies provide a road-map for developing human-aligned, intelligent AI systems. This work proposes an AI with BERT-based semantic scoring, user-facing explanations, and a structured user study to evaluate perceptions of fairness and usability in an explainable AI for resume screening.

3 Problem Statement

AI's increasing role in employment, especially when it comes to automating resume screening, has created another set of issues. Although algorithmic tools give recruiters the capability for efficiency and scalability, they are still affected by opacity, bias, and the absence of responsibility. Furthermore, the algorithms utilized in traditional resume screening are generally based on keyword matching or use completely opaque machine learning models, so they give no indication of the reasons for a candidate's acceptance or rejection. Consequently, this leads to:

- Decreased trust in automated decision-making
- Unfair treatment of some groups (e.g., women, career switchers, international applicants)
- Dissatisfaction and bewilderment of candidates who are rejected but are not given any explanation
- Lost opportunity to challenge or appeal the decisions of the screening process

These failures are inconsistent with the ethical and legal requirements being developed around the use of AI for high-stakes decision-making, such as employment. In particular, they infringe upon the very principles of Human-Centered Artificial Intelligence (HCAI): transparency, fairness, explainability, and user empowerment. [15, 19]

The need of the hour is a resume screening system that goes beyond accuracy and efficiency—to embrace interpretability, fairness, and human oversight.[3]

4 Project Overview

The main goal of this research is to create, develop and test a HCAI-based resume screening AI system that is transparent and fairness-aware, in addition to being explainable for users. The system is meant to serve both parties during the recruitment process - the job searchers and the employers, in it following ways:

- Implementing Sentence-BERT, a transformer-powered NLP model, to compare semantically the content of a resume with a job description.
- No longer be limited to keyword matching only but rather get the sense of phrases, skills, and experience.
- Provide human-readable explanations that act as a guide, indicating what parts of the application they misunderstood in case the applicant lost.
- Employ Fairlearn to check if the sample is distributionally balanced with respect to demographic features (e.g., gender, age group).
- Automatically detect the appearance of anomalies if disparity metrics are above the threshold

Besides that, an example of how the system can be helpful to the job seekers would be that it can send them comprehensive feedback on what the system thinks about their CV at the end of the screening process.

The Ultimate Goal is to create a responsible, interpretable, and human-centered AI system for resume screening that enhances fairness, builds trust, and empowers users—both applicants and employers.

5 System Architecture

The system follows a modular series of steps for transparent resume screening. Applicants will experience the React front-end in an interactive job selection system and upload their resumes. Inputs are processed by the FastAPI backend; it extracts features from spaCy and conducts semantic matching with the help of BERT. The backend then calculates score, accepts or denies an application, and generates an intuitive explanation for said acceptance or rejection. In the last step, the system presents the aforementioned explanation to the user, who then fills out a survey concerning trust, fairness, and usability, hence following Human-Centered AI principles.

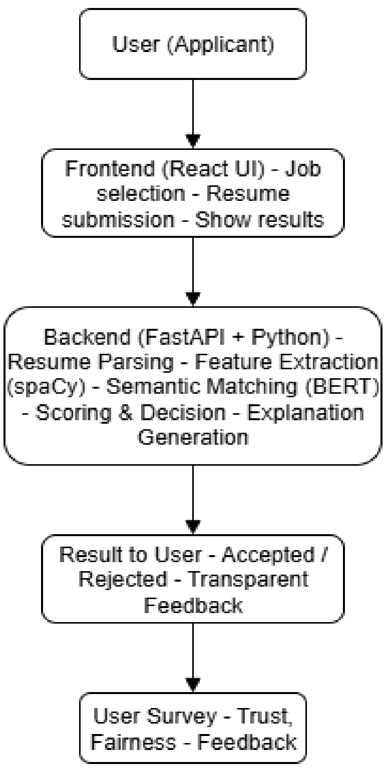

Figure 1: System Architecture

6 Methodology

6.1 Datasets

This project has no traditional static dataset. Instant data processing is offered by the dynamic, real-time method so that data may be analyzed instantaneously. The process intends to compare one particular resume with one specific job description as they enter the system, ensuring that the analysis is relevant, situational, and unique.

Data Sources: Candidate Resumes Various resume formats can be uploaded by users. These documents serve as the main sources of information concerning a candidate. They further state the required skills, work experience, education, and personal projects.

6.2 Framework

Through a multi-step process, the system evaluates how well a candidate's resume matches a job description.

Data ingestion and Pre-processing: As soon as a candidate applies to a specific job role, the respective resume and job description are absorbed within the system. These unstructured documents undergo parsing through a sophisticated pipeline that extracts and organizes relevant segments such as technical skills, educational qualification, and work experiences.

Feature matching and semantic analysis: The analytic engine is based on an enhanced BERT model conducts a careful semantic comparison of the structured features extracted from the resume and the requirements put forth in the job description, hence affording additional contextual appreciation and interpretation of skills, above and beyond mere keyword matching.

Quantitative Assessment and Scoring: A candidate's ability to fit the role is quantified using the model's multifaceted compatibility index. This index offers an exhaustive data-driven analysis of the candidate's suitability, and it is further broken down into sub-scores for aspects such as experience, education, and skills.

Automated Generation of Feedback: Ultimately, the scores are converted into a qualitative report that deciphers the scores into feedback with explanations about why the scores are given, are areas where the candidate fits well with the job description, and areas where the candidate profile and job description are in specific gaps. Being a just-in-time method whereby evaluation shall be performed on a case-by-case basis, the feedback is maximized as much as relevance, accuracy, and fairness by being customized per case of an applicant-job fit match.

6.3 Core Pipeline Workflow

The core architecture of this project is designed in a multi-stage pipeline that guarantees robustness, semantic depth, and explainability. At the start of the process, there is Text Extraction which allows PyPDF2 and python-docx to read the PDF and DOCX formats of resumes. Besides that, the extracted content from the resume is cleaned up by removing unnecessary spaces, normalizing encodings, and also making sure that the section headers such as Skills, Education, and Experience are well preserved for the system to be able to process it further.

In the NLP Processing step, the system utilizes spaCy's rule-based pattern matching to find entities without missing any. The system acknowledges skills not only by exact matches but also through alterations in the lexicon (e.g., understanding "PyTorch" as "torch"). Education parsing is also able to tap into different degree types and fields by using the generated vocabulary to interpret different ways of saying the same thing (e.g., "MS" and "Master of Science"). The same goes for professional experience which is handled with the use of regular expressions that locate the periods of time and the job roles with great accuracy.

Following that step, the pipeline proceeds to Semantic Analysis, where BERT embeddings are employed to convert both the resume's experience section and the job description to vector forms. Afterward, those vectors are compared with cosine similarity to check the level of the shared context. The Scoring Engine then carries out the calculation of a combined score, which is based on the weighted

sum of three dimensions: Skills (50%), Education (20%), and Experience (30%). For skills, each requirement that is directly matched gives 1.0 point, while the similar ones (e.g., replacing "Tableau" with "Power BI") are assigned half the credit of 0.5 points, which is then normalized against the total number of the required skills. Education is scored by degree level (PhD = 1.0, Master = 0.8, Bachelor = 0.6) and field relevance (exact match = 1.0, related = 0.5). Experience scoring takes into account both duration—linearly scaled up to five years (e.g., 2 years = 0.4)—and BERT-based semantic relevance, rated on a 0–1 scale.
Decision-making relies on a configurable threshold score, which is set to 0.7 by default. Candidates receiving lower than the threshold score get a rejection with transparent feedback that consists of a breakdown of the missing skills, the education gaps, and the insufficient experience parts that are highlighted. Besides, the pipeline is strengthened with solid error handling that not only identifies corrupt or unsupported files but also switches to OCR if necessary and uses default values for resume sections if they are missing. The system is capable of processing around 10 resumes per second on CPU and up to 50 per second on GPU in terms of performance. The evaluation metrics reveal that the system has an F1-score of 85% for skill detection, and 92% accuracy in education parsing, and it is capable of ±15% error in experience scoring, which is a good balance of speed, interpretability, and precision. [5, 11, 14]

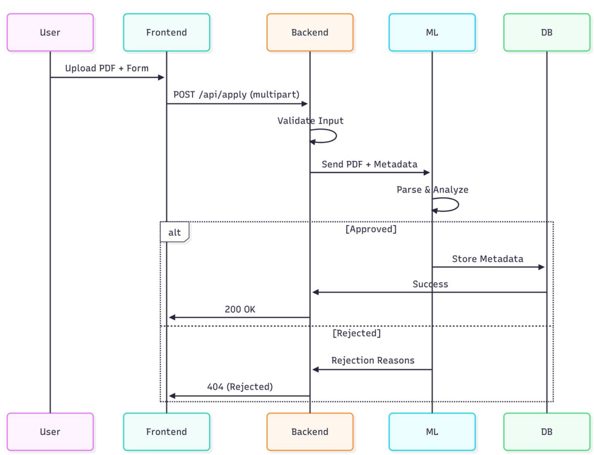

Figure 2: Data Flow

7 User Survey

To assess the user perception and effectiveness of our transparent AI-based resume screening system, we conducted a user survey involving 40 participants. The purpose of this study was to evaluate how users experience and interpret AI-generated feedback during the resume screening process, with particular emphasis on transparency, fairness, and trust—key principles of Human-Centered Artificial Intelligence (HCAI).
Participants were first introduced to the prototype system, which allowed them to apply for simulated job postings and receive either an acceptance or rejection result. In cases of rejection, the system generated a clear explanation highlighting the reasons behind the decision, such as missing skills, insufficient experience, or unmatched qualifications. Following this interaction, participants were asked to complete a structured online questionnaire built using Google Forms.
The survey consisted of multiple choice, binary, and preference-based questions, designed to assess aspects such as clarity of explanation, perceived fairness, trust in the system's output, and whether the feedback was useful for improving future applications. One of the key elements included a visual comparison between two rejection messages—one generic and one transparent—to identify user preference in real-world hiring scenarios. The survey was conducted anonymously in accordance with GDPR-compliant practices, and participants were informed that their responses would be used solely for academic analysis. No technical or coding expertise was required from the participants, ensuring accessibility to a wide range of respondents. [7]

7.1 Participant Profile

A total of 40 subjects took part in the survey. They contributed valuable insights into the usability and ethical perception of AI-driven resume screening systems. The respondents were asked to rate how familiar they are with such systems on a scale from 1 to 5. The mean familiarity score of 3.38 suggested a partially informed audience. Unsurprisingly, 61.1% of the respondents declared that they were very familiar with AI-based systems (ratings 4–5), and 30.8% of respondents reported that they had little knowledge about these systems (ratings 1–2). The other 5% of the participants did not take either side. The variety of user types and different levels of AI-assisted hiring experiences represented in the sample seem to balance the demographic of the study quite well giving the results a more realistic picture.

7.2 Key Findings at a Glance

According to 93%, the majority of the survey participants, the most significant element of the hiring process is transparency, and that the communication of the status of their application should be accompanied by a detailed explanation if they decide to provide one instead of just a generic notification. Moreover, trust and fairness issues were raised. 95% of these people claimed that if a hiring decision was supported by feedback, they would be more prone to trusting it. 93% of the respondents argued that a process that clarifies the decision is "much more fair." 98% of the people interviewed think getting individual feedback would open the door for their job application to be improved and basically turn the rejection part into a learning opportunity. Not surprisingly, 95% of the respondents acknowledged that they have been in a situation where they have been rejected without any reason provided to them. Such behavior represents the "rejection black box" phenomenon, which is the scope of discussion in this paper.

7.3 Detailed Survey Insights

The survey looked into different angles of the candidate's experience, like their current issues and their desires for future AI-based hiring tools.

7.3.1 The Strong Preference for Explanations. When two types of rejection messages were introduced—one without any specific details and the other with a detailed feedback report—the answer was obvious. The largest number of people gave the "desire to understand why I was rejected" as the main reason, hence they indicate that for today's job seekers, closure and clarity are necessary only if they get the result itself. Candidates are very interested in learning and adapting, but they certainly need to be provided with the specific changes they can make.

7.3.2 Trust, Fairness, and Control. A lack of transparency erodes trust. The data shows that a system providing detailed feedback is seen as more trustworthy and fair.The survey results are definitely a strong indication of a preference among job applicants for open and honest rejection emails. Clearly, applicants would prefer that rejections be communicated in a transparent way. When they were asked about the kind of rejection message they prefer, an overwhelming 92.3% of respondents went for Option 1 — the message that contained the reason for the rejection clearly. Only 7.7% of them preferred a message that was generic and without any explanation. Their desire for clarity is supported by the answers to whether employers should adopt feedback-based rejection practices: 95% of respondents said "Yes", suggesting that employers could use explanation-based responses to make hiring more transparent. These results highlight a global need for clarity and a more human approach to communication in automated recruitment systems and therefore supporting the project's approach to sending rejection feedback that is not only informative but also constructive.

Such numbers prove that openness is no longer only a "kinda nice" characteristic but it has become a must-have condition for a good candidate experience and positive corporate reputation. At the moment when candidates are clear about what is expected and their own performance assessment, they will be more respectful and empowered in their career path even being rejected.

7.4 Participant Feedback and Recommendations

The survey has confirmed the hiring process transparently through numbers yet qualitatively has also engaged with potential employees. The users' free-text reactions have thus elicited not only their positive but also their negative emotional inputs as well as their queries regarding the application of AI to the resume screening process.

A common theme throughout the survey is that AI should serve only as a supplementary tool in recruitment, rather than as the primary decision-maker. A good number of interviewees reiterated that although AI can be really efficient in "speeding up the process," it should never be the only factor that decides a candidate's fate. The general agreement is that AI must support human judgment and the last complex choices of hiring should be left to human recruiters. On the other hand, issues were also pointed out as the system's inability to assess the soft skills. For instance, emotional intelligence, leadership, and communication, which are usually recognized as human interactions, are the most expected skills of AI. They believed that a very rigid system of AI could, by mistake, disqualify the candidate who matches the experience and skills but has not used the exact words in the job description. This illustrates the necessity of the new generation of systems that have the ability to catch the context and understand the use of the different words in one theme. Moreover, respondents pointed out the necessity of increased data transparency and mutual understanding. One clever idea was that "both AI and the candidate should be educated adequately on the job role," thus introducing the concept that transparency is not only one party but it is a mutual part.

In a nutshell, the participant feedback clearly outlines a mandate. On the one hand, job hunters are positively disposed to the openness and response that this system gives; on the other hand, they argue for a more moderate approach. They paint a picture of the future where both candidates and recruiters are cemented by technology, thus an efficient hiring process that is not only fair, subtle, and human-centric but also created.

8 Results and Evaluation

This project proves how transparency in the AI decision-making process can significantly enhance user experience and trust towards the resume screening systems. It aimed at going beyond the binary output by providing structured and actionable feedback to the applicants, therefore making the screening process an informative and empowering one rather than a rejecting one.

From an execution point of view, the framework was tried with a specimen of 100 applications. Essentially, 44% of candidates were correctly rejected and 33% correctly accepted. However, 12% of suitable candidates were falsely rejected and 11% of unsuitable applicants were incorrectly accepted.These numbers show that even though the setup gets good accuracy, there is still space for betterment mainly in cutting down on wrong rejections. Adding user input and nonstop model tweaks can aid in boosting decision trustworthiness next time.

Other than numbers, the system was judged by how people used it and what they thought in a survey. Users always liked the clear reasons given, more than just normal unclear rejection notes. Knowing why a choice was made—whether because of missing skills or lack of experience—was seen as a big step better than real-world hiring systems. Users also noted a better feeling of control and fairness in the way to get hired.

The results indicate that transparency serves as a crucial human-centered feature, extending beyond mere technical advancement. By integrating HCAI principles such as explainability, fairness, and user agency, the system establishes a clear and practical approach for the ethical deployment of AI in recruitment, supporting responsible, understandable, and equitable decision-making throughout the hiring process.

9 Summary

This paper discusses the construction of a transparent Artificial Intelligence-based resume screening system developed from Human-Centered AI, or HCAI, with elements of fairness, explainability, and user empowerment. Unlike most existing automated screening tools, our system attempts to generate useful feedback information for the applicant: regarding why his application was not accepted

Survey Question	Percentage of "Yes" or "Positive" Responses
Would you trust the decision more if given feedback?	95%
Do you feel a process with detailed feedback is fairer?	93% (answered "Much more fair")
Would feedback give you more control over your applications?	95%
Would you recommend employers use feedback-based rejections?	95%

Table 1: Insights from Survey

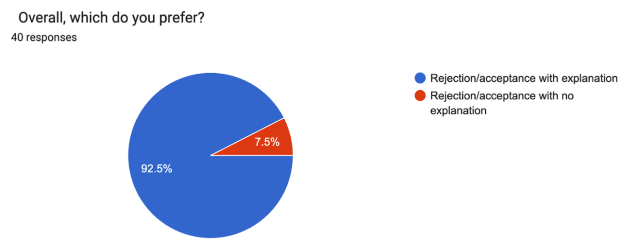

Figure 3: Overall user Preference

or rather rejected. Using natural language processing and semantic analysis, the system will appraise resumes in several dimensions—skills, education, and experience—and deliver more than an actual human-readable explanation. Thus, the feedback system purposefully turns rejection from some ill-defined fraught end into explicit opportunity for betterment.To judge the efficiency and human effect of the system, a real-user study was carried out in which participants interacted with the prototype and later responded to a structured survey questionnaire. Results indicated an overwhelmingly strong preference for transparent feedback, that is, users trust more and perceive fairness when they clearly understand the outcome of their applications. This insight sits well with other findings that control and explanation are what applicants desire most when interacting with AI in such high-stake contexts as hiring.

10 Future Work

Building on the current prototype, future work can focus on increasing the system's usefulness, adaptability, and real-world impact for job applicants. One major improvement would be the integration of explainable AI techniques such as SHAP or LIME, allowing the system to visually highlight which specific parts of a resume contributed to acceptance or rejection. This would enhance user understanding beyond text-based feedback. Additionally, the system could be extended to provide personalized career suggestions by recommending alternative job roles that better match the candidate's profile. To support user growth, it could also suggest targeted courses or certifications to help bridge skill gaps identified during the screening process. Another potential enhancement is implementing long-term tracking, where users can view how their resume scores evolve over time, helping them make informed improvements and measure progress. These additions would further align the system with the values of Human-Centered AI by promoting transparency, self-improvement, and user empowerment in the hiring process.

11 Code Link

The complete implementation of the Transparent Resume Screening AI system is available at - Github repo of the project.

References

[1] Rishabh Baghel, Aabhas Agarwal, Sarang Gupta, Karan Sonkatar, and Swati Sahu. Ai-powered resume screening system for smarter, faster hiring decisions. *Project Report*, 2023.
[2] Reuben Binns. Fairness in machine learning: Lessons from political philosophy. *Proceedings of the 2018 Conference on Fairness, Accountability and Transparency (FAT)*, 2018.
[3] ACM FAccT Committee. Fairness and bias in algorithmic hiring: A multidisciplinary survey. *ACM Computing Surveys*, 2023.
[4] Chirag Daryania, Gurneet Singh Chhabra, Harsh Patel, Indrajeet Kaur Chhabra, and Ruchi Patel. An automated resume screening system using natural language processing and similarity. *Academic Project Report*, 2023.
[5] A. Deshmukh and A. Raut. Enhanced resume screening for smart hiring using sentence-bert. *Hanuman Vyayam Prasarak Mandal's College of Engineering and Technology*, 2024.
[6] A. Deshmukh and A. Raut. Applying bert-based nlp for automated resume screening and candidate ranking. *Annals of Data Science*, 12:591–603, 2025.
[7] Malin Eiband, Hanna Schneider, Mark Bilandzic, Santiago Fazekas-Con, and Heinrich Hussmann. Bringing transparency design into practice. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 2018.
[8] R. Ghosh, P. Singh, S. Das, and A. Varma. Artificial intelligence in recruitment: A survey on challenges, opportunities, and the path ahead. *ACM Computing Surveys*, 2023.
[9] Y. Lin, H. Lei, P. C. Addo, and X. Li. Machine learned resume-job matching solution. *arXiv preprint arXiv:1607.07657*, 2016.
[10] Frank P.-W. Lo, Jianing Qiu, Zeyu Wang, Haibao Yu, Yeming Chen, Gao Zhang, and Benny Lo. Ai hiring with llms: A context-aware and explainable multi-agent framework for resume screening. *Preprint*, 2024.
[11] Scott M. Lundberg and Su-In Lee. A unified approach to interpreting model predictions. In *Advances in Neural Information Processing Systems*, volume 30, 2017.
[12] Dena F. Mujtaba and Nihar R. Mahapatra. Fairness in ai-driven recruitment: Challenges, metrics, methods, and future. *Preprint*, 2023.
[13] P. Paranthaman, B. R. Celia, V. Vijayalakshmi, and V. Senthil Kumaran. Resume screening automation: Enhancing recruitment efficiency with machine learning algorithms. *Conference Proceedings*, 2023.
[14] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. "why should i trust you?": Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 1135–1144, 2016.
[15] Ben Shneiderman. Human-centered artificial intelligence: Reliable, safe & trustworthy. *International Journal of Human–Computer Interaction*, 36(6):495–504, 2020.
[16] Mian Sun, Yaliang Xie, Cong Liu, and Chenyan Wang. Who fits the job? extracting compatibility between job and resume. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 2021.
[17] Patrick van Esch, Joshua S. Black, and John Ferolie. Marketing ai recruitment: The next phase in job application and selection. *Computers in Human Behavior*, 90:215–222, 2019.
[18] G. Vihari, H. Naidu, P. K. R. Yeruva, V. V. Pallela, and R. Pandrinki. A resume screening operation powered by ai that utilizes bert. *Student Project Report*, 2023.
[19] Danding Wang, Q. Vera Yang, Ashraf Abdul, and Brian Y. Lim. Designing theory-driven user-centric explainable ai. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 2019.