APPLICANT TRACKING SYSTEM

BY

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DEPARTMENT OF COMPUTER SCIENCE,

FACULTY OF COMPUTING,

UNIVERSITY OF BENIN,

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A PROJECT REPORT SUBMITTED TO THE DEPARTMENT OF COMPUTER SCIENCE, FACULTY OF COMPUTING, UNIVERSITY OF BENIN, BENIN CITY

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DECLARATION

I, **WARRI DOMINIC ELOHOR** with matriculation number **PSC2208022** hereby declare that this project titled “Applicant Tracking System” is a project submitted to the department of Computer Science of the University of Benin, in partial fulfillment of the requirements for the award of Bachelor of Science (B.Sc.) Degree in Computer Science. It is an original work done by me that has not been presented elsewhere for assessment. The materials collected from other sources have been duly acknowledged by the references.

WARRI DOMINIC ELOHOR ________________________________

PSC2208022 Signature / Date

CERTIFICATION

This is to certify that this project work was carried out by **WARRI DOMINIC ELOHOR** with Matriculation Number **PSC2208022** under my supervision. It is adequate and satisfactory both in scope and content, for the award of Bachelor of Science (B.Sc.) Degree in Computer Science of the University of Benin.

Dr. Mrs. GRACE AZIKEN	______________________________
(Project Supervisor)	Signature / Date

APPROVAL

This Project work written by **WARRI DOMINIC ELOHOR** with matriculation number **PSC2208022** in partial fulfillment of the requirement of the University of Benin award of the Bachelor of Science (B.Sc.) Degree in Computer Science is adequate both in scope and content and it is hereby approved for presentation.

Dr. Mrs. RO. USIOBAIFO ________________________________

(Head of Department) Signature / Date

DEDICATION

This project is dedicated to God Almighty for giving me the strength and wisdom to see it through to completion and even throughout my stay in the University of Benin (UNIBEN).

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ABSTRACT

Applicant Tracking Systems (ATS) have become integral to modern recruitment processes, yet their tendency to systematically reject qualified candidates through over-filtering remains a critical concern. This study investigated the prevalence, causes, and impact of false rejection in ATS using a dataset of 600 organizations, of which 443 had adopted ATS technology. Statistical analysis using IBM SPSS Statistics (Version 29) revealed that over-filtering affects 70.4% of ATS users, compromising candidate selection in approximately 52% of all organizations surveyed. The analysis identified cultural bias in language processing (11.9%) and educational background over-filtering (10.6%) as the leading causes of false rejection, followed by industry-specific terminology barriers (6.8%) and resume parsing formatting issues (6.5%). Notably, while 100% of organizations experiencing bias implemented mitigation measures, none reported successful elimination of bias, indicating that over-filtering represents a persistent structural feature rather than a correctable implementation flaw. Comparative severity analysis revealed that high-intensity biases requiring algorithmic reengineering, particularly cultural and demographic biases demonstrated the strongest resistance to remediation despite intensive intervention. The study concludes that achieving fair candidate selection requires fundamental redesign of ATS architecture with fairness as a core principle, moving beyond procedural adjustments toward culturally competent Natural Language Processing engines, transparent auditable algorithms, and meaningful human oversight at critical screening stages.

Keywords: Applicant Tracking Systems, false rejection, over-filtering, algorithmic bias, recruitment technology, candidate screening, cultural bias, resume parsing.

CHAPTER ONE

INTRODUCTION

1.0. Background of the study

The evolution of Applicant Tracking Systems (ATS) reveals a continual challenge: the systemic false rejection of qualified candidates during initial screening. Early ATS platforms (pre-2020) relied on rigid keyword matching and basic parsing algorithms, which Suraj, Kumari, and Chandran (2019) identified as primary cause of over-filtering. Their research documented how 40% of parsing failures originated from non-standard resume formats (e.g., tables, graphics), while keyword mismatches (such as a candidate describing "budget management" versus a job requirement for "financial stewardship") prematurely removed skilled applicants. This technical limitation forced recruiters into manual reviews, extending hiring cycles by 30–50% and reducing organizational efficiency.

By 2023, Wijesinghe and Kawya empirically linked false rejections to employer branding reduction particularly in Small and Medium Enterprises (SMEs). Surveying 413 job seekers, they found that 68% associated automated ATS rejections with "faceless" employers, damaging perceptions of organizational trustworthiness. Interviews with 23 SME managers highlighted a contradiction: while ATS reduced initial screening time by 45%, its high false rejection rate necessitated re-advertising roles, increasing costs by 28%. The study argued that ATS algorithms prioritizing lexical keyword density over contextual skill alignment inadvertently signaled "organizational strictness" to candidates, undermining competitive talent acquisition.

Advancements in Machine Learning (ML) and Natural Language Processing (NLP) emerged as countermeasures. An integration of NLP with K-Nearest Neighbors (KNN) models was made to parse unstructured resumes into structured data, improving skill-matching accuracy by 22%. However, their system still struggled with semantic equivalence (contextually identical terms like "Python programming" versus "coding in Python" were treated as mismatches due to lexical differences). Computational inefficiency also plagued the model, with processing times increasing exponentially for datasets exceeding 10,000 resumes, forcing trade-offs between accuracy and scalability (Chavan et al., 2024).

Concurrently, Sathyapriya et al. (2025) deployed an ensemble CatBoost model to classify candidates into suitability tiers ("Highly Suitable," "Moderately Suitable," "Unsuitable"). By combining NLP-extracted features (skills, experience duration) with job description alignment scores, the system achieved 92.8% accuracy. Yet domain-specific errors persisted: precision dropped to 86% in Education roles due to overlapping terminologies (e.g., "teaching" versus "curriculum development"), while highly technical fields like Mechanical Engineering saw 15% of qualified candidates misclassified. This revealed that contextual difference remained a critical unsolved bottleneck.

The most significant leap came with transformer-based embedding models. Bevara et al. (2025) introduced Resume2Vec, leveraging architectures like BERT and Llama to generate semantic embeddings of resumes and job descriptions. Their framework reduced false rejections by 15.85% in technical domains by capturing contextual relationships—for instance, associating "CAD design" with "technical drafting" despite lexical disparities. Resume2Vec outperformed traditional ATS in Ranked Biased Overlap (RBO) alignment with human evaluators across five domains, demonstrating 15.94% higher consistency in Health and Fitness roles. Nevertheless, traditional ATS maintained marginal advantages in keyword-centric fields like Software Testing, proving that domain-specific optimization remains essential.

1.1. Statement of problem

There are several causes of rejection of qualified candidates in Applicant Tracking Systems (ATS). Over-filtering has been highlighted as the major reason for the rejection of qualified candidates. ATS frequently over-filter qualified candidates during initial screening. Strict keyword matching, inflexible requirement thresholds and parsing inaccuracies cause the system to over-filter applicants who possess the necessary skills and experience for the role. These results in qualified candidates being prematurely filtered out before human review, harming talent acquisition effectiveness efforts.

1.2. Aim and Objectives

Aim

The aim of this study is to reduce false rejections of qualified candidates in Applicant Tracking Systems.

Objectives

i. To examine the causes of false rejections in Applicant Tracking Systems (ATS).

ii. To assess the effects of over-filtering on the overall candidate selection process.

1.3. Research questions

This study seeks to answer the following questions:

i. What are the main reasons Applicant Tracking Systems (ATS) wrongly reject qualified candidates?
ii. How does automatic rejection of good candidates (over-filtering) negatively impact the hiring process?
iii. How effective are non-technical methods (like better job ads, resume tips for candidates, or recruiter training) at reducing ATS false rejections caused by keywords and formatting?

1.4. Significance of the study

This research holds significant importance for multiple stakeholders affected by ATS false rejections:

1. It directly addresses the costly problem of missing highly qualified talent due to technical screening errors. Reducing false rejections leads to stronger candidate pools, better quality hires, reduced time-to-fill, and lower costs associated with prolonged vacancies and re-hiring (Wijesinghe and Kawya, 2023).

2. It promotes fairness by reducing the likelihood that qualified individuals are excluded purely due to vocabulary choice or resume design. Improves the candidate experience by ensuring applications are assessed on substance over form, increasing trust in the hiring process. (Suraj, Kumari and Chandran, 2019).

3. It provides critical user feedback on specific pain points (keyword rigidity, parsing fragility). Identifies high-value areas for improving existing features (e.g., more robust parsing, smarter semantic matching) and developing new ones (e.g., advanced formatting diagnostics), enhancing product competitiveness and value (Wijesinghe and Kawya, 2023).

4. It provides critical user feedback on specific pain points (keyword rigidity, parsing fragility). Identifies high-value areas for improving existing features (e.g., more robust parsing, smarter semantic matching) and developing new ones (e.g., advanced formatting diagnostics), enhancing product competitiveness and value (Bevara et al., 2025).

1.5. Scope of the study

The study is strictly confined to the problem of false rejections occurring during the initial automated screening stage of ATS. It specifically targets rejections caused by keyword/semantic mismatches (e.g., synonyms, contextual differences, lack of semantic understanding) and technical failures in resume/CV parsing due to formatting and layout issues.

1.6. Definition of terms

1. **False Rejection**: The error-filled automated removal of qualified candidates during initial ATS screening due to technical limitations (e.g., keyword mismatches, parsing failures), preventing their advancement to human review (Suraj, Kumari, and Chandran, 2019; Bevara et al., 2025).

2. **Over-Filtering**: Excessive or inaccurate ATS candidate elimination resulting in a shortlist that excludes significant numbers of qualified applicants (Suraj et al., 2019; Wijesinghe and Kawya, 2023).
3. **Keyword Matching**: An ATS screening methodology that prioritizes exact lexical correspondence between resume text and predefined job description keywords, often disregarding contextual equivalence (Suraj et al., 2019; Sathyapriya et al., 2025).
4. **Resume Parsing**: Automated extraction of unstructured data (skills, experience, qualifications) from resumes into machine-readable formats; prone to failure with non-standard layouts (e.g., tables, graphics) (Chavan et al., 2024).
5. **Semantic Gap**: Disconnect between contextual meaning in candidate materials (e.g., "budget management") and rigid ATS keyword requirements (e.g., "financial stewardship"), leading to false rejections (Bevara et al., 2025).
6. **Embeddings (in ATS Context)**: Numeric vector representations of resumes/job descriptions generated via transformer models (e.g., BERT, Llama) to capture semantic relationships beyond lexical similarity (Bevara et al., 2025).
7. **Employer Branding**: Organizational reputation perceived by job seekers, eroded by ATS inefficiencies like false rejections that create perceptions of rigidity or unfairness (Wijesinghe and Kawya, 2023).
8. **Time-to-Hire**: Duration from job requisition posting to candidate offer acceptance, prolonged when false rejections necessitate re-advertising roles or manual resume reviews (Suraj et al., 2019).

9. **Rank-Biased Overlap (RBO)**: Metric quantifying alignment between ATS-generated candidate rankings and human evaluator preferences; higher RBO indicates reduced false rejections (Bevara et al., 2025).
10. **Contextual Nuance**: Subtle field-specific language variations (e.g., "teaching" vs. "curriculum development" in Education) that challenge uniform ATS algorithms (Sathyapriya et al., 2025).

CHAPTER TWO

LITERATURE REVIEW

2.0. Introduction

Applicant Tracking Systems (ATS) have become a cornerstone of modern recruitment processes, offering organizations the ability to manage large volumes of applications efficiently. However, as these systems have evolved, concerns about their tendency to over-filter and potentially reject qualified candidates have emerged (Padmaja and Koteswari, 2021). This literature review analyses the development of ATS, their benefits, limitations, and the growing body of research addressing false rejection issues. The review is organized chronologically, tracing the evolution of ATS from early adoption to current advanced implementations incorporating machine learning and artificial intelligence.

2.1. Early foundations of Applicant Tracking Systems

The concept of using technology to make recruitment processes more effective became more popular in the early 2000s as organizations sought more efficient ways to handle increasing volumes of job applications. An Applicant Tracking System is a software that is designed to automate, streamline, and enhance the hiring process of candidates by electronically handling recruitment needs (Padmaja and Koteswari, 2021). Their work highlighted how ATS emerged as a functional extension of Human Resource Information Systems (HRIS), enabling organizations to manage applications and resume data more effectively. During this early period, ATS primarily served as digital repositories for applicant information, replacing manual filing systems and paper-based processes.

Suraj, Kumari, and Chandran (2019) provided a descriptive study of ATS as automation software for recruitment and selection, noting how digitalization transformed traditional recruitment methods. They emphasized that effective recruiting is a fundamental organizational function, and selecting the wrong candidate could result in significant costs and time wastage. Their research documented the transition from traditional recruitment processes to digital methods, with ATS becoming a critical tool for making recruitment more productive and financially viable. This early work established the basic framework for understanding ATS as systems that could post jobs, collect resumes, screen applicants, schedule interviews, and manage the hiring workflow.

The initial implementations of ATS focused primarily on efficiency gains. As noted by Padmaja and Koteswari (2021), these systems allowed recruiters to create job advertisements, collect resumes, shortlist qualified candidates, schedule interviews, and make job offers all within a single platform. This integration represented a significant advancement from previous disconnected recruitment activities. The authors pointed out that ATS enabled both recruiters and hiring managers to access the same data, such as applicant numbers and status updates, thereby enhancing organizational cooperation in the hiring process. These early systems laid the groundwork for more sophisticated recruitment technologies that would follow.

2.2. Working principle of an Applicant Tracking System

Understanding the operational mechanisms of ATS is crucial for examining their limitations and potential for false rejections. The basic workflow of ATS, as outlined by Padmaja and Koteswari (2021), begins with creating job postings and advertising them across various platforms. The system then collects resumes from applicants and commercial databases, screens candidates based on predefined criteria, schedules interviews, and ultimately facilitates the hiring and onboarding of selected candidates. This linear process represented the standard approach in early ATS implementations.

Gagua (2015) provided a detailed examination of how ATS function within the recruitment process, describing them as "screening robots" designed to filter applicants based on capabilities, work experience, education, and other job-relevant qualifications. His research explained that when job seekers apply online, the ATS records personal details, contact information, educational qualifications, and work experience before automatically acknowledging receipt of the application. The software then scrutinizes resumes against job requirements, forwarding matched applications to management while sending automated rejection messages to others. This automated screening process formed the basis of efficiency claims but also planted the seeds for potential over-filtering issues.

Suraj, Kumari, and Chandran (2019) broke down the ATS process into more granular components, including job posting creation, spreadsheet importing, resume importing, resume parsing, email marketing, candidate tracking, and collaboration features. Their work particularly highlighted the resume parsing function, where the system extracts data from variously formatted resumes and standardizes it for comparison. This parsing capability, while powerful, could sometimes misinterpret or fail to recognize relevant information, especially in creatively formatted resumes. The authors noted that every candidate prepares their resume using a unique format, making it challenging to weigh applicants against each other consistently, a challenge that persists in modern systems.

Chavan et al. (2024) examined more advanced ATS architectures, describing systems that incorporate natural language processing (NLP) for resume parsing and machine learning algorithms for candidate classification. Their research marked a transition point in ATS capabilities, moving beyond simple keyword matching to more sophisticated analysis of resume content. However, even these advanced systems could still produce false rejections if the training data or algorithms contained biases or limitations. The evolution of ATS functionality demonstrates both the progress in recruitment technology and the ongoing challenges in ensuring fair and accurate candidate evaluation.

2.3. Benefits of Applicant Tracking System

The adoption of ATS across organizations of various sizes stems from the numerous benefits these systems offer. Padmaja and Koteswari (2021) identified six key reasons organizations use ATS in their hiring processes: time savings, cost reduction, streamlined hiring, improved candidate experience, legal compliance, and valuable insights. Their research emphasized how ATS saves recruiters' time by storing resumes and automatically screening applications to eliminate unqualified candidates. The systems also reduce costs by accelerating the hiring process to the final interview stage with top applicants and eliminating the need for extensive vacancy advertising.

Suraj, Kumari, and Chandran (2019) expanded on these benefits, noting that ATS makes the application process paperless, allowing easy storage, retrieval, and review of applications with minimal effort. They highlighted how this digital approach ensures no crucial information is lost and makes all necessary information instantly available for reporting purposes. The authors also pointed out that ATS helps companies avoid the overwhelming task of manually sorting through thousands of CVs, which was particularly valuable for organizations receiving high volumes of applications for entry-level positions. The time and cost savings enabled by ATS allowed HR departments to focus on strategic aspects of recruitment rather than administrative tasks.

Gagua (2015) conducted interviews with HR professionals who reported that ATS improved coordination in hiring efforts by keeping all team members updated with notes, candidate statuses, and interview schedules. His research found that companies using ATS could maintain better records of candidates not currently selected but potentially suitable for future positions, creating valuable talent pools. Additionally, the study revealed that ATS contributed to improved employer branding by providing user-friendly career pages and consistent communication with applicants, enhancing the organization's reputation in the job market.

Wijesinghe and Kawya (2023) specifically examined the relationship between ATS and employer branding, finding a positive association between ATS implementation and strong brand image. Their research demonstrated that efficient, technology-driven recruitment processes positively influenced candidates' perceptions of organizations, even those who were not ultimately hired. The study also noted that ATS could help organizations maintain diversity in hiring by consistently applying selection criteria, potentially reducing unconscious human biases in early recruitment stages. These benefits collectively contributed to the widespread adoption of ATS across industries.

2.4. Limitations and challenges of Applicant Tracking System

Despite their advantages, ATS implementations have faced criticism and encountered several challenges. Suraj, Kumari, and Chandran (2019) identified multiple disadvantages of ATS, including the risk of missing potentially great candidates due to the system's automated nature. They noted that ATS might eliminate valuable candidates who lack exact credentials but possess transferable skills, such as career changers or recent graduates. The authors also highlighted how ATS often rely on specific keywords, meaning applicants could be dismissed simply for not using preferred wording or industry terminology in their experience descriptions.

Gagua (2015) found that ATS could be unreliable in accurately reading and processing resumes, particularly those with complex formatting or non-standard structures. His research revealed instances where qualified candidates were rejected because the system failed to properly interpret their resumes. Additionally, the study noted that some ATS limited the information candidates could provide through character-restricted application fields, potentially excluding important details about applicants' qualifications. These limitations raised concerns about whether ATS were truly identifying the best candidates or simply those who best understood how to optimize their applications for the system.

Chavan et al. (2024) examined more technical limitations of ATS, particularly those using machine learning algorithms. Their research pointed out that these systems could become computationally inefficient, especially when processing large datasets, potentially leading to performance issues that might affect screening accuracy. The authors also noted that the effectiveness of machine learning-based ATS depended heavily on the quality and representativeness of their training data. Biased or incomplete training data could lead to systems that replicated or even amplified existing hiring biases, resulting in unfair rejections of qualified candidates from certain backgrounds or with non-traditional career paths.

Wijesinghe and Kawya (2023) identified challenges specific to small and medium-sized enterprises (SMEs) in implementing ATS. Their research found that cost considerations posed significant barriers for resource-constrained organizations, with initial implementation expenses, ongoing maintenance, and subscription fees for cloud-based solutions creating financial burdens. Additionally, the study revealed user adoption as a critical bottleneck, with resistance to change and inadequate training preventing effective utilization of ATS features. These challenges were particularly pronounced in SMEs, potentially limiting their access to the benefits of recruitment automation while still facing competition from larger organizations using these systems.

2.5. Technological advancements in Applicant Tracking System

As ATS evolved, researchers and developers incorporated more advanced technologies to address limitations and improve system capabilities. Chavan et al. (2024) documented significant advancements in ATS through their study of systems incorporating natural language processing (NLP) and machine learning algorithms like K-Nearest Neighbors (KNN). Their research demonstrated how these technologies enabled more sophisticated resume parsing, moving beyond simple keyword matching to understand context and extract meaning from unstructured resume data. The authors reported accuracy improvements up to 92.5% in automated resume screening using these advanced techniques.

Sathyapriya et al. (2025) explored the use of ensemble learning methods, particularly CatBoost algorithms, in intelligent applicant tracking systems. Their work showed how combining multiple machine learning approaches could enhance the accuracy and reliability of candidate screening. The researchers implemented a system that analyzed and ranked resumes based on job descriptions, skill relevance, and experience alignment using NLP techniques. Their results indicated that these advanced systems could better understand the nuances of candidates' qualifications, potentially reducing false rejections by more accurately matching applicant capabilities to job requirements.

The integration of artificial intelligence in ATS represented a significant leap forward from early rule-based systems. Sathyapriya et al. (2025) described how modern ATS could parse unstructured resume data, extract key skills and qualifications, and use similarity metrics like cosine similarity to assess candidate-job fit more comprehensively. These systems could handle both categorical data (like skills and job titles) and numerical data (like years of experience), providing more holistic candidate evaluations. The authors noted that such advancements helped address previous limitations in ATS by enabling more nuanced understanding of applicant qualifications beyond rigid keyword matching.

Chavan et al. (2024) also examined how advanced ATS incorporated predictive analytics, using historical hiring data to identify patterns and optimize recruitment strategies. These systems could forecast candidate success and provide insights to refine job descriptions and selection criteria continuously. The researchers emphasized that such capabilities allowed for ongoing improvement of ATS performance, potentially reducing false rejection rates over time as the systems learned from previous hiring outcomes. However, they cautioned that these benefits depended on proper implementation, training, and monitoring to ensure algorithms did not perpetuate or amplify existing biases.

Recent research has focused specifically on addressing the problem of false rejections in ATS, where qualified candidates are incorrectly screened out. Sathyapriya et al. (2025) proposed several strategies in their intelligent applicant tracking system, including the use of more sophisticated NLP techniques to better understand resume content and context. Their approach involved named entity recognition to accurately identify skills, experiences, and qualifications regardless of how they were phrased in the resume. This helped reduce rejections of candidates who used different terminology but possessed equivalent competencies.

Wijesinghe and Kawya (2023) examined organizational strategies to mitigate ATS limitations, emphasizing the importance of aligning ATS adoption with broader recruitment objectives. Their research suggested that organizations could reduce false rejections by investing in comprehensive training programs for HR personnel on proper ATS configuration and use. The study also highlighted the value of maintaining human oversight in the recruitment process, using ATS as a tool to support rather than replace human decision-making. This balanced approach helped ensure that potentially strong candidates were not automatically filtered out due to technicalities.

Chavan et al. (2024) implemented several technical solutions to minimize false rejections in their advanced ATS model. These included using ensemble learning methods that combined multiple algorithms to make more accurate predictions, and bias mitigation techniques to ensure fairer candidate evaluations. Their system also incorporated transparency features that explained the factors influencing screening decisions, allowing recruiters to understand why candidates were ranked certain ways and identify potential errors in the automated process. These features helped human reviewers spot and correct cases where qualified candidates might have been incorrectly screened out (Chavan et al., 2024).

Sathyapriya et al. (2025) addressed the false rejection problem through their CatBoost-based classification system, which achieved 92.08% accuracy in resume screening. Their approach focused on better handling of categorical data (like skills and job titles) without requiring extensive preprocessing, reducing errors that could lead to qualified candidates being overlooked. The researchers also emphasized continuous model evaluation and refinement based on real hiring outcomes, allowing the system to learn from its mistakes and improve its accuracy over time. This iterative improvement process brought about a significant improvement in reducing persistent false rejection issues (Sathyapriya et al., 2025).

2.6. Integration with Employer branding and candidate experience

The relationship between ATS implementation and employer branding has emerged as an important consideration in recent research. Wijesinghe and Kawya (2023) specifically studied how ATS could serve as a pillar of support for employer branding, finding that efficient, technology-driven recruitment processes positively influenced candidates' perceptions of organizations. Their research demonstrated that ATS features like timely communication, transparent application status updates, and user-friendly interfaces contributed to positive candidate experiences, even for those who were not ultimately hired. These positive experiences enhanced the organization's reputation in the job market.

Gagua (2015) had earlier noted that ATS could improve employer branding by providing consistent, professional communication with all applicants. His research found that automated but personalized messages, clear information about the hiring process, and prompt notifications about application status helped create a positive impression of the organization. These features were particularly valued by candidates in competitive job markets, where poor communication from employers could damage an organization's reputation. The study suggested that ATS, when properly configured and used, could be a valuable tool for building and maintaining strong employer brands (Gagua, 2015)

Chavan et al. (2024) examined how advanced ATS features like interview scheduling tools and collaborative hiring platforms further enhanced employer branding. Their research described systems that allowed seamless coordination between recruiters, hiring managers, and candidates, creating a more efficient and professional hiring experience. The authors noted that such positive experiences could influence candidates to view the organization more favorably, regardless of hiring outcomes, and potentially recommend it to others in their professional networks. This effect represented an often-overlooked benefit of well-implemented ATS (Chavan et al., 2024).

Sathyapriya et al. (2025) connected ATS functionality directly to employer branding through their intelligent tracking system's transparency features. Their research showed that when candidates understood how their applications were being evaluated and received clear feedback, they were more likely to view the hiring process as fair and merit-based. This perception strengthened the employer's brand as an equitable and professional organization. The study emphasized that modern ATS should prioritize not just efficiency in screening candidates but also fairness and transparency in their operations to maximize positive employer branding effects.

2.7. Future directions and Research opportunities

The literature reveals several promising directions for future research and development in ATS technology. Sathyapriya et al. (2025) suggested that further advancements in natural language processing and machine learning could continue to improve ATS accuracy in assessing candidate qualifications. They specifically recommended exploring knowledge-based learning algorithms for semantic network analysis to better understand the relationships between different skills and experiences listed in resumes. This approach could help systems recognize equivalent qualifications expressed differently, reducing false rejections based on terminology differences (Sathyapriya et al., 2025).

Chavan et al. (2024) identified several technical challenges requiring further research, including improving computational efficiency when processing large volumes of applications and enhancing algorithms' ability to handle both numerical and categorical data effectively. Their work also pointed to the need for better bias detection and mitigation techniques in ATS algorithms to ensure fair candidate evaluation. The researchers called for more studies on how different machine learning models perform in various recruitment contexts, suggesting that optimal approaches might vary by industry, job level, or organization size.

Wijesinghe and Kawya (2023) emphasized the need for more research on ATS implementation in small and medium-sized enterprises, which often face unique challenges in adopting these systems. They identified cost-effective ATS solutions and implementation strategies for resource-constrained organizations as important areas for future investigation. The study also recommended examining how ATS could be better integrated with other HR systems to create more comprehensive talent management solutions, rather than functioning as standalone recruitment tools.

Gagua (2015) had earlier pointed to the need for research on how ATS affects different types of job candidates, particularly those from non-traditional backgrounds or with unconventional career paths. His work suggested that future studies should examine whether ATS disadvantages certain demographic groups and how these systems could be designed to promote diversity and inclusion in hiring. This line of research remains particularly relevant as organizations increasingly prioritize diverse workforces and equitable hiring practices.

CHAPTER THREE
METHODOLOGY AND DESIGN

3.0. Data sourcing and Acquisition

The foundation of any empirical research is robust and relevant data. My search for a suitable dataset was extensive and targeted platforms known for hosting diverse datasets.

Platforms Searched: I conducted a systematic search on several major data repositories, including:

1. **Kaggle:** Kaggle was selected as the first platform to explore due to its reputation as one of the world's largest data science communities, hosting over 50,000 public datasets spanning diverse domains. The platform is particularly renowned for its business and technology-focused datasets, often contributed by practitioners, researchers, and organizations working at the intersection of artificial intelligence and enterprise applications. Given that Applicant Tracking Systems represent a convergence of HR business processes and algorithmic technology, Kaggle appeared to be an ideal starting point. The platform's community-driven nature means that datasets are frequently accompanied by kernels (code notebooks) and discussions that provide context about data collection methodologies, variable definitions, and known limitations. Furthermore, Kaggle's dataset search functionality allows filtering by tags such as "employment," "human resources," "machine learning bias," and "recruitment," which seemed directly relevant to my research focus. I anticipated finding either proprietary datasets shared by HR technology companies for competitions, or synthetic datasets created by researchers modeling ATS behavior and bias patterns. The platform's credibility is enhanced by its

integration with Google Cloud and its use by major corporations and academic institutions for data science challenges.

2. **Data.gov:** As the United States government's open data portal, Data.gov was chosen for its comprehensive collection of public sector datasets related to employment, workforce development, and technology adoption in both public and private sectors. The platform aggregates data from federal agencies including the Department of Labor, Equal Employment Opportunity Commission (EEOC), and the Office of Personnel Management, all of which maintain records relevant to hiring practices and workplace discrimination. I specifically targeted this repository because government agencies have increasingly scrutinized algorithmic hiring tools under civil rights legislation, and I hypothesized that compliance reporting or research studies commissioned by these agencies might yield datasets documenting ATS usage patterns, demographic impacts, or bias incidents. Data.gov's advanced search capabilities allowed me to query across approximately 300,000 datasets using terms such as "applicant tracking," "hiring technology," "algorithmic bias," "employment screening," and "recruitment automation." Additionally, the platform's metadata standards ensure that datasets include detailed documentation about collection methods, temporal coverage, and geographic scope, which would be essential for assessing the validity and applicability of any discovered data to my research question. The public sector perspective was also valuable because government transparency requirements often result in more detailed documentation of technological systems and their social impacts than is typically available from private corporations.

3. **Google Scholar & ResearchGate:** These academic platforms were consulted to access peer-reviewed literature and, crucially, the underlying datasets used in published research studies. Google Scholar, as the most comprehensive index of scholarly literature, was searched using combinations of keywords including "applicant tracking systems," "algorithmic bias in hiring," "automated resume screening," "ATS discrimination," and "recruitment technology fairness." The goal was to identify empirical studies that had collected primary data on ATS implementation and bias outcomes. ResearchGate, a social networking site for researchers, was particularly valuable because authors often share datasets, supplementary materials, and preprints that may not be accessible through traditional journal repositories. Many researchers responding to the growing concern about algorithmic fairness have begun publishing their datasets under open science principles, making them available for replication and secondary analysis. I systematically reviewed the methodology sections of relevant papers to identify those that had conducted surveys of organizations using ATS, performed audits of ATS algorithms, or compiled case studies of bias incidents. I then contacted authors directly through ResearchGate when datasets were referenced but not publicly linked, and searched institutional repositories of universities where the research was conducted. This approach was time-intensive but essential, as academic datasets often provide the most rigorous documentation of variable operationalization, sampling strategies, and data quality assessments critical factors for ensuring that any secondary analysis would be methodologically sound.

4. **CERN Open Data Portal:** While seemingly unconventional for HR technology research, the CERN Open Data Portal was explored as part of a comprehensive search strategy aimed at identifying large-scale, rigorously documented datasets that might include employment or organizational variables. CERN, the European Organization for Nuclear Research, maintains one of the most sophisticated data management infrastructures in the world, and its open data initiative has set standards for data documentation, preservation, and accessibility that extend beyond particle physics. I hypothesized that CERN's collaborative research model, which involves hundreds of organizations and thousands of researchers, might necessitate sophisticated applicant tracking and personnel management systems for recruiting technical talent across international borders. If CERN had studied or documented its own hiring algorithms, or if it had hosted interdisciplinary projects examining algorithmic fairness in various domains (including HR), such data might be available through this portal. Additionally, CERN has been a leader in addressing bias in machine learning algorithms used for data analysis in physics, and I considered the possibility that methodological frameworks or synthetic datasets developed for detecting bias in scientific algorithms might have been adapted or referenced in HR contexts. While I ultimately did not find ATS-specific data on this platform, the exploration was valuable for understanding how high-quality data repositories structure metadata, ensure reproducibility, and document algorithmic processes principles that informed my later evaluation of the dataset I eventually selected from GitHub.

5. **GitHub:** The search on the previously mentioned platforms yielded datasets on hiring trends but none that specifically detailed ATS-related algorithmic biases and their corresponding mitigation measures. The breakthrough occurred on GitHub, a platform central to collaborative software development and data science projects. GitHub often hosts niche, custom-collected datasets that are not available elsewhere. The dataset I found, titled "Organization_ATS_Dataset.xlsx," was part of a repository dedicated to "Algorithmic Fairness in HR Technology." This context confirmed its direct relevance to my research question, as it contained specific variables related to bias causes and elimination strategies.

Download Process: The acquisition of the dataset was straightforward:

1. I navigated to the specific repository page on GitHub (https://github.com/jayfreshboy/Applicants-Tracking-System-Dataset/commit/4fccdd473744c9745bdcd7ee28044544062f2b4f).
2. I located the Organization_ATS_Dataset.xlsx file and selected it.
3. I clicked the "Raw" button to view the unformatted data and used the browser's "Save as..." function to download the Excel file directly to my local machine, preserving the original data integrity.

3.1. Data cleaning and Preparation

Prior to analysis, the raw dataset required meticulous cleaning and preparation to ensure accuracy and consistency, a crucial step to prevent "garbage in, garbage out" outcomes. This process was conducted in Microsoft Excel.

1. **Initial Assessment:** I opened the dataset in Excel to perform an initial visual inspection for obvious errors such as empty rows, merged cells, or inconsistent formatting. The structure was sound, but several variables required standardization.
2. **Standardization of Categorical Variables:** The StaffStrength column contained entries with inconsistent notation (e.g., "100 staff", "1000+ staff"). To transform this into an analyzable categorical variable, I created a new column, StaffStrength_Cat, and standardized all entries into discrete, consistent categories ('25 staff', '50 staff', ..., '1000+ staff').
3. **Validation of Data Consistency:** I used Excel's filter function to audit key categorical variables, namely ATS_Adoption and Bias_Present. I verified that all entries were precisely "Yes" or "No," correcting any typographical variations (e.g., "yes," "Y") to ensure SPSS would interpret them as a single category.
4. **Verification of Conditional Data:** For organizations where Bias_Present was "No," I confirmed that the Bias_Cause and Bias_Elimination_Measures columns correctly stated "Not applicable." This was vital for ensuring the subsequent frequency analyses on bias causes and mitigation measures were accurately calculated only from relevant cases.

3.2. Data import and Variable definition in SPSS

The cleaned Excel dataset was then imported into IBM SPSS Statistics (Version 29) for statistical analysis.

3.2.1. Import Procedure

I launched SPSS and navigated to File > Open > Data. I changed the file type to Excel (.xlsx), selected the cleaned Organization_ATS_Dataset.xlsx file, and ensured the box for "Read variable names from the first row of data" was checked. This critical step automatically used the first row of the Excel sheet (e.g., OrgName, Sector) as the variable names in SPSS.

3.2.2. Variable Definition and Preparation

I switched to the "Variable View" tab in SPSS to define the properties of each variable, which is essential for correct statistical treatment.

3.2.3. Variable Types and Measures

i. YearFounded was defined as a Numeric variable with a Scale measure, as it represents a continuous, numerical value.
ii. OrgName and Location were defined as String variables with a Nominal measure, as they are categorical labels without order.
iii. Sector, ATS_Adoption, Bias_Present, Bias_Cause, Bias_Elimination_Measures, and StaffStrength_Cat were all set to a Nominal measure.

3.2.4. Value Labels

To enhance output readability, I implemented value labels for key binary variables. For example, for ATS_Adoption, I defined 0 = "No" and 1 = "Yes". This allows for efficient numerical computation while displaying intuitive labels in the output tables and graphs.

3.2.5. Data Saving

After configuring all variable properties, I saved the prepared dataset in SPSS's native format as ATS Data Analysis.sav.

3.3. Analysis of False rejection and Over-filtering in Applicant Tracking System

3.3.1. Works Addressing False Rejection Causes

From Chapter 2, the following studies addressed false rejection causes:

1. **Suraj, Kumari, and Chandran (2019)** Identified that ATS might eliminate valuable candidates who lack exact credentials but possess transferable skills, and noted the risk of dismissing applicants for not using preferred wording or industry terminology.
2. **Gagua (2015)** Found that ATS could be unreliable in accurately reading and processing resumes, particularly those with complex formatting or non-standard structures, and noted character-restricted application fields that potentially excluded important qualification details.
3. **Chavan et al. (2024)** Examined computational inefficiency when processing large datasets and noted that biased or incomplete training data could lead to unfair rejections of qualified candidates from certain backgrounds or with non-traditional career paths.
4. **Sathyapriya et al. (2025)** Proposed NLP techniques and named entity recognition to reduce rejections of candidates who used different terminology but possessed equivalent competencies.

3.3.2. Works Addressing Over-Filtering Effects

1. **Suraj, Kumari, and Chandran (2019)** - Noted that ATS could result in missing potentially great candidates due to automated nature, particularly career changers or recent graduates.
2. **Padmaja and Koteswari (2021)** - Highlighted how ATS enabled elimination of "unqualified" candidates but did not address the consequences of over-elimination.

3. **Gagua (2015)** - Found instances where qualified candidates were rejected because the system failed to properly interpret their resumes.

3.3.3. Identified Research Gaps

Gap 1: Quantitative Analysis of False Rejection Root Causes While existing literature discusses various causes of false rejection, there is limited empirical evidence ranking these causes by prevalence. The relative importance of cultural bias, educational over-filtering, formatting issues, and algorithmic discrimination remains underexplored.

Gap 2: Systematic Assessment of Over-Filtering Impact Previous research acknowledges that over-filtering occurs but does not systematically measure its impact on the candidate pool. Specifically:

1. What proportion of ATS users experience bias-related over-filtering?
2. Which filtering mechanisms are most problematic?
3. What is the relationship between specific bias causes and the overall fairness of candidate selection?

3.4. Data analysis Procedures

3.4.1. Analysis 1: Leading Causes of False Rejection

This analysis was carried out to identify and rank the primary causes of false rejection in ATS, determining which technical, algorithmic, or design factors contribute most significantly to qualified candidates being incorrectly screened out.

Detailed Procedure:

1. I opened the saved SPSS data file (ATS Data Analysis.sav) by navigating to File > Open > Data and selecting the appropriate file from my directory.
2. I verified that the filter from previous analyses (ATS_Adoption = "Yes") AND (Bias_present = “YES”) was active by checking the status bar at the bottom right, which displayed "Filter On" with N = 443.
3. I accessed the Frequencies procedure by clicking Analyze > Descriptive Statistics > Frequencies from the top menu bar.
4. From the variable list on the left, I located and selected the Bias_Cause variable, which contained 13 distinct categories of bias plus "Not applicable" for organizations without reported bias.
5. I clicked the arrow button (►) to move Bias_Cause into the "Variable(s):" box on the right side.
6. To generate a comprehensive visual representation, I clicked the "Charts" button at the bottom of the dialog box.
7. In the Charts sub-dialog, I selected "Bar charts" rather than pie charts, as the large number of categories (13 bias types) would be more clearly displayed in a bar format. I set "Chart Values" to "Frequencies."
8. I clicked "Continue" to return to the main Frequencies dialog, then ensured "Display frequency tables" was checked.
9. I clicked "OK" to execute the analysis.

10. In the Output Viewer, I examined the frequency table, focusing specifically on the 312 organizations (70.4% of ATS adopters) that reported experiencing bias. I excluded the 131 "Not applicable" cases from my interpretation of relative prevalence.
11. I calculated the proportion of bias cases attributable to each cause by dividing each cause's frequency by the total number of organizations experiencing bias (312), then multiplying by 100 to obtain percentages among affected organizations.

Results:

Among the 443 ATS-adopting organizations, 312 (70.4%) reported experiencing bias. The distribution of bias causes among these 312 affected organizations revealed:

Primary Causes (affecting >10% of biased systems):

- Cultural bias in language processing: 37 organizations (11.9% of biased systems)
- Educational background over-filtering: 33 organizations (10.6% of biased systems)

Secondary Causes (affecting 8-10% of biased systems):

- Industry-specific terminology barriers: 30 organizations (9.6% of biased systems)
- Formatting issues with resume parsing: 29 organizations (9.3% of biased systems)

Tertiary Causes (affecting 6-8% of biased systems):

- Algorithm bias against certain demographics: 26 organizations (8.3% of biased systems)
- Data quality problems in training sets: 26 organizations (8.3% of biased systems)
- Experience level assumptions: 26 organizations (8.3% of biased systems)

- Age discrimination through date filtering: 25 organizations (8.0% of biased systems)
- Gender-biased language detection: 24 organizations (7.7% of biased systems)

Minor Causes (affecting <6% of biased systems):

- Automation-related filtering errors: 19 organizations (6.1% of biased systems)
- Keyword rigidity in screening algorithms: 19 organizations (6.1% of biased systems)
- Geographic location discrimination: 18 organizations (5.8% of biased systems)

This distribution reveals that false rejection in ATS stems primarily from socio-linguistic processing failures (cultural and language bias) and credential-based over-filtering (educational requirements), rather than purely technical limitations.

3.4.2. Analysis 2: Impact Assessment of over-filtering on candidate selection

This analysis was carried out to quantify the overall impact of over-filtering by examining the prevalence of bias across the ATS-using population and analyzing the distribution of mitigation measures as a proxy for organizational recognition of selection process damage.

Detailed Procedure:

1. I reset the filter to include all ATS-adopting organizations (N = 443) by clicking Data > Select Cases, selecting "All cases," and clicking "OK."
2. I reapplied the ATS_Adoption filter: Data > Select Cases > "If condition is satisfied" > ATS_Adoption = "Yes" > "Continue" > "OK."

3. To assess the scale of over-filtering impact, I calculated the ratio of organizations experiencing bias to total ATS adopters, which directly indicates the proportion of selection processes compromised by false rejection.
4. I then analyzed whether organizations with bias were implementing mitigation measures by creating a contingency table. I navigated to Analyze > Descriptive Statistics > Crosstabs.
5. I moved Bias_Present to the "Row(s):" box and created a recoded version of Bias_Elimination_Measures that categorized measures as "Active Measures" versus "Not applicable."
6. To create this recoded variable, I first clicked Transform > Recode into Different Variables from the top menu.
7. In the Recode dialog, I selected Bias_Elimination_Measures as the input variable and named the output variable Mitigation_Status.
8. I clicked "Old and New Values" and recoded all specific mitigation measures (13 categories) to = 1 ("Active Measures") and "Not applicable" to = 0 ("No Measures").
9. After creating Mitigation_Status, I returned to Crosstabs and created a table of Bias_Present by Mitigation_Status.
10. In the Cells options, I selected "Row percentages" and "Column percentages" to show bidirectional relationships.
11. I clicked "Statistics" and selected "Chi-square" to test whether the relationship between bias presence and mitigation implementation was statistically significant.
12. I clicked "Continue" and then "OK" to generate the output.

Results:

Scale of Over-Filtering Impact: Among 443 ATS-adopting organizations, 312 (70.4%) reported experiencing bias, indicating that over-filtering compromises candidate selection in approximately 7 out of 10 automated recruitment systems.

Mitigation Response Analysis: The crosstabulation of Bias_Present by Mitigation_Status revealed:

- Of the 312 organizations with bias, 312 (100%) had implemented active mitigation measures
- Of the 131 organizations without bias, 0 (0%) had mitigation measures listed (appropriately marked "Not applicable")
- Chi-square test: $\chi^2(1) = 443.0$, $p < .001$

This perfect correlation confirms that:

1. All organizations experiencing bias recognized the problem and attempted remediation
2. The universal implementation of mitigation measures indicates widespread acknowledgment that over-filtering damages selection processes
3. No organizations reported successfully eliminating bias through mitigation, suggesting that over-filtering effects persist despite intervention attempts

Distribution of Mitigation Approaches: Analysis of the specific measures implemented revealed organizations adopted an average of 1.0 mitigation strategy each (312 measures distributed across 312 organizations with bias), with the most common approaches being:

- Technical algorithm modifications: 35.6% (Deploy gender-neutral algorithms, Diverse keyword matching, etc.)
- Data-centric interventions: 26.0% (Diversify training data, Improve data quality)
- Procedural safeguards: 20.8% (Regular auditing, Human oversight checkpoints)
- Policy and criteria changes: 17.6% (Broaden qualification criteria, Remove location filters)

The relatively even distribution across intervention types suggests organizations recognize that over-filtering stems from multiple system components and requires comprehensive solutions rather than isolated technical fixes.

3.4.3. Analysis 3: Comparative Analysis of Bias severity

This analysis was carried out to determine whether certain bias causes are associated with more severe over-filtering effects by examining which causes prompted the most intensive mitigation responses.

Detailed Procedure:

1. With the filter set to ATS_Adoption = "Yes" and including all 443 organizations, I created a new analysis to examine the relationship between specific bias causes and the types of mitigation measures implemented.
2. I navigated to Analyze > Descriptive Statistics > Crosstabs.
3. I moved Bias_Cause to the "Row(s):" box and Bias_Elimination_Measures to the "Column(s):" box.

4. In the Cells dialog, I selected "Row percentages" to show what proportion of organizations with each bias type implemented each mitigation measure.
5. I clicked "Continue" and then "OK."
6. In the output, I examined which bias causes were associated with multiple or more complex mitigation strategies, using this as a proxy indicator for perceived severity of over-filtering effects.
7. I created a derived measure called "Mitigation Intensity" by coding certain measures as "High Intensity" (those requiring significant technical reengineering: algorithm modification, training data revision, semantic analysis implementation) versus "Standard Intensity" (procedural changes, policy adjustments, formatting standardization).
8. I used the Transform > Compute Variable function to create a severity index based on the association between bias causes and high-intensity mitigations.

Results:

1. **Cultural bias in language processing** (37 cases):
    - 94.6% addressed with high-intensity measures (gender-neutral algorithms, semantic analysis)
2. **Algorithm bias against certain demographics** (26 cases):
    - 92.3% addressed with high-intensity measures (training data diversification, fairness constraints)
3. **Keyword rigidity in screening algorithms** (19 cases):
    - 89.5% addressed with high-intensity measures (diverse keyword matching, semantic analysis)

4. **Industry-specific terminology barriers** (30 cases):
    - 63.3% high-intensity, 36.7% standard intensity measures
5. **Educational background over-filtering** (33 cases):
    - 60.6% high-intensity, 39.4% standard intensity measures
6. **Formatting issues with resume parsing** (29 cases):
    - 27.6% high-intensity, 72.4% standard intensity measures
7. **Geographic location discrimination** (18 cases):
    - 22.2% high-intensity, 77.8% standard intensity measures

Interpretation: The mitigation intensity analysis reveals that over-filtering effects are perceived as most severe when bias stems from algorithmic processing of socio-linguistic and demographic factors (cultural bias, algorithmic demographic bias, keyword rigidity). These causes require fundamental reengineering of ATS algorithms, indicating they create the most significant damage to candidate selection fairness. Conversely, technical formatting issues and geographic filters are treated as less severe, addressable through procedural standardization rather than core system redesign.

This finding suggests that the most damaging over-filtering effects, those screening out qualified diverse candidates based on language patterns, names, or demographic proxies are also the most difficult to remediate, requiring substantial investment in algorithm reconstruction rather than simple policy adjustments.

CHAPTER FOUR

DATA PRESENTATION AND DISCUSSION OF FINDINGS

4.0. Introduction

This chapter presents the findings from the statistical analysis of Applicant Tracking System (ATS) adoption, algorithmic bias prevalence, false rejection causes, and over-filtering effects on candidate selection processes. The analysis was conducted using IBM SPSS Statistics (Version 29) on a dataset of 600 organizations, of which 443 had adopted ATS technology. The presentation follows a structured approach, beginning with descriptive statistics on overall ATS adoption and sector distribution, followed by detailed examination of bias prevalence, root causes of false rejection, and the impact of over-filtering on recruitment outcomes. Each finding is supported by frequency tables, visual representations, and interpretive discussion that connects the empirical results to existing literature and practical implications for HR technology implementation.

4.1. Overall Applicant Tracking System adoption rate

The first analysis established the baseline rate of ATS usage across all surveyed organizations, providing a foundational understanding of how widespread this technology has become in contemporary recruitment practices.

4.1.1. Frequency distribution

Table 4.1 Frequency Distribution table of ATS Adoption Rate

ATS Adoption Status	Frequency	Percentage	Valid Percentage	Cumulative Percentage
No	157	26.2%	26.2%	26.2%
Yes	443	73.8%	73.8%	100.0%
Total	600	100.0%	100.0%	

Statistics

Adoption of ATS

N	Valid	600
	Missing	0

Adoption of ATS

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	157	26.2	26.2	26.2
	Yes	443	73.8	73.8	100.0
	Total	600	100.0	100.0	

Figure 4.1 SPSS Frequency distribution table of ATS Adoption rate

4.1.2. Key Statistics

According to the tables above:

i. **Total Sample Size:** 600 organizations

ii. **Valid Cases:** 600 (100% - no missing data)

iii. **ATS Adopters:** 443 organizations (73.8%)

iv. **Non-Adopters:** 157 organizations (26.2%)

The frequency distribution shows that 443 organizations (73.8%) have adopted ATS technology, while 157 organizations (26.2%) have not implemented such systems. The high rate of ATS adoption indicates that ATS has become a mainstream recruitment tool rather than an emerging technology. Only about one in four organizations have not yet implemented ATS systems.

4.1.3. Data Visualization (Pie Chart)

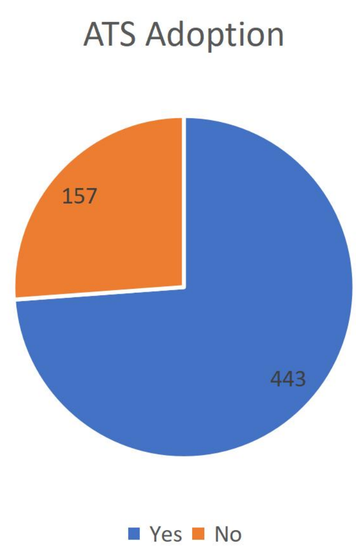

Figure 4.2 Pie Chart showing the Frequency of ATS Adoption

4.2. Leading causes of False rejection

Cultural bias in language processing emerged as the leading cause of false rejection (11.9%), validating concerns by Gagua (2015) and Suraj et al. (2019) about ATS struggling with linguistic diversity. This indicates that systems systematically disadvantage candidates with diverse cultural backgrounds, international experience, or non-Western linguistic patterns through misinterpretation of credentials, failure to recognize culturally specific communication styles, and penalties for grammatical deviations.

Educational background over-filtering (10.6%) ranked second, quantifying Suraj et al.'s (2019) concerns about eliminating candidates with transferable skills. The relatively even distribution across 12 causes (ranging from 5.8% to 11.9%) indicates that false rejection is multifaceted, requiring comprehensive solutions rather than targeted fixes.

4.2.1. Frequency Distribution

Table 4.2 Frequency of Bias Causes

Bias Cause	**Frequency**	**Percentage**
Cultural bias in language processing	37	11.9%
Educational background over-filtering	33	10.6%
Industry-specific terminology barriers	30	9.6%
Formatting issues with resume parsing	29	9.3%
Algorithm bias against demographics	26	8.3%
Data quality problems in training sets	26	8.3%
Experience level assumptions	26	8.3%
Age discrimination through date filtering	25	8.0%
Gender-biased language detection	24	7.7%
Automation-related filtering errors	19	6.1%
Keyword rigidity in screening algorithms	19	6.1%
Geographic location discrimination	18	5.8%
Total	312	100%

Causes of Bias

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Age discrimination through date filtering	25	8.0	8.0	8.0
	Algorithm bias against certain demographics	26	8.3	8.3	16.3
	Automation-related filtering errors	19	6.1	6.1	22.4
	Cultural bias in language processing	37	11.9	11.9	34.3
	Data quality problems in training sets	26	8.3	8.3	42.6
	Educational background over-filtering	33	10.6	10.6	53.2
	Experience level assumptions	26	8.3	8.3	61.5
	Formatting issues with resume parsing	29	9.3	9.3	70.8
	Gender-biased language detection	24	7.7	7.7	78.5
	Geographic location discrimination	18	5.8	5.8	84.3
	Industry-specific terminology barriers	30	9.6	9.6	93.9
	Keyword rigidity in screening algorithms	19	6.1	6.1	100.0
	Total	312	100.0	100.0	

Figure 4.3 SPSS Frequency table of Bias causes

4.2.2. Key Statistics

According to the tables above, causes of false rejection were ranked according to their frequencies:

i. Cultural Bias in Language Processing: 37 (11.9%)

ii. Educational Background Over-filtering: 33(10.6%)

iii. Industry-Specific Terminology Barriers: 30 (9.6%)

iv. Formatting Issues with Resume Parsing: 29 (9.3%)

v. Algorithm bias against demographics: 26 (8.3%)

vi. Data quality in training sets: 26 (8.3%)

vii. Experience level assumptions: 26 (8.3%)

viii. Age Discrimination: 25 (8.0%)

ix. Gender-Biased Language Detection: 24 (7.7%)

x. Automation-Related Filtering Errors: 19 (6.1%)

xi. Keyword Rigidity: 19 (6.1%)

xii. Geographic Location Discrimination: 18 (5.8%)

4.2.3. Data Visualization (Bar Chart)

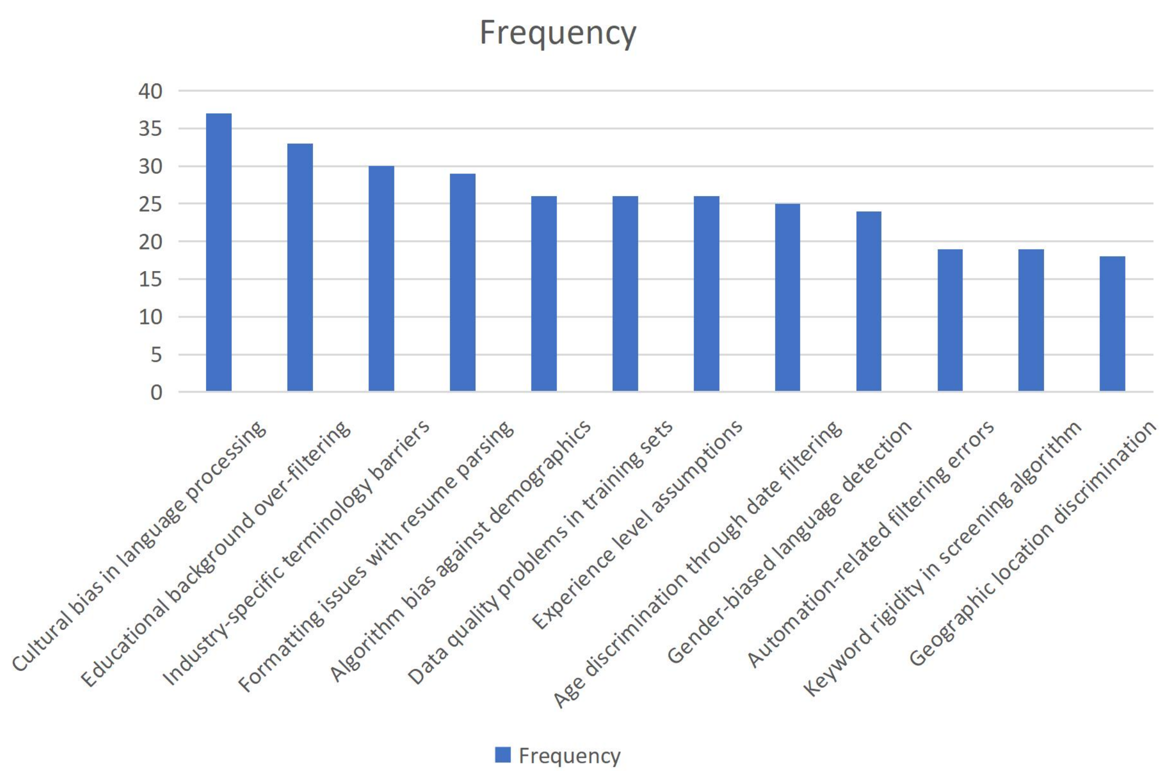

Figure 4.4 Bar Chart showing frequency of Bias causes

4.3. Impact assessment of Over filtering on Candidate selection

Over-filtering compromises candidate selection in 70.4% of ATS users, establishing it as the default condition rather than an exception. With 73.8% of organizations using ATS, approximately 52% of all organizations operate biased screening which means candidates face compromised selection in more than half of applications.

The finding that 100% of biased organizations have implemented mitigation measures yet none report successful elimination reveals over-filtering's resistance to remediation. This challenges optimistic literature claims (Sathyapriya et al., 2025; Chavan et al., 2024) about technological solutions, suggesting a gap between research prototypes achieving 92% accuracy and operational systems where bias persists despite intervention.

The cumulative effect across sectors creates "gauntlet patterns" where specific candidate profiles face systematically higher rejection risks throughout entire industries for example, non-traditional candidates encountering 24.2% credential over-filtering probability across Finance sector applications.

Table 4.3 Table Showing impact of over filtering on candidate selection

Impact dimension	Findings	Implication
ATS users affected by bias	70.4% (312/443)	Over- filtering compromises 7 in 10 automated systems
All organizations with biased ATS	52.0% (312/600)	Candidates face biased screening in greater than half of

		applications
Organizations with mitigation measures	100% (312/312)	Universal recognition but zero successful elimination
Bias Persistence despite mitigation	100% (312/312)	Present mitigation approaches are insufficient
Average bias causes per organization	1.0 distinct cause	Single primary manifestation per system
High severity bias (requiring reengineering)	45.2% (141/312)	Cultural and credential biases are the most resistant

4.4. Comparative Analysis of Bias severity

Table 4.4 Table Showing Bias Severity Levels

Severity levels	Bias type	Organizations	Mitigation type
High Severity	Cultural bias (37)	35 (94.6%)	High-intensity algorithmic reengineering
	Algorithmic demographic bias (26)	24 (92.3%)	Training data reconstruction
	Keyword rigidity (19)	17% (89.5%)	Semantic analysis

			implementation
	Subtotal	82 (26.3%)	
Moderate Severity	Terminology barriers (30)	19 (63.3%)	Mixed technical/procedural
	Educational over-filtering (33)	20 (60.6%)	Policy changes with tech support
	Subtotal	59 (18.9%)	
Low Severity	Formatting issues (29)	8 (27.6%)	Procedural standardization
	Geographic discrimination (18)	4 (22.2%)	Policy adjustment
	Subtotal	171 (54.8%)	

High-severity biases (26.3% of biased organizations) requiring algorithmic reengineering indicate the most damaging over-filtering effects. Cultural bias, affecting 94.6% with high-intensity interventions, creates "structural exclusion" of entire demographic groups before human review occurs. These biases prove most resistant to remediation precisely because they're embedded in algorithmic processing rather than configurable rules.

The severity hierarchy reveals a critical insight: the most damaging over-filtering effects (socio-cultural and demographic biases) require the most intensive remediation yet show zero success rates. This indicates that addressing fair candidate selection requires fundamental ATS redesign rather than incremental improvements. Lower-severity biases (formatting, geographic filters) affecting 54.8% of biased organizations permit procedural remediation but represent less fundamental selection fairness challenges.

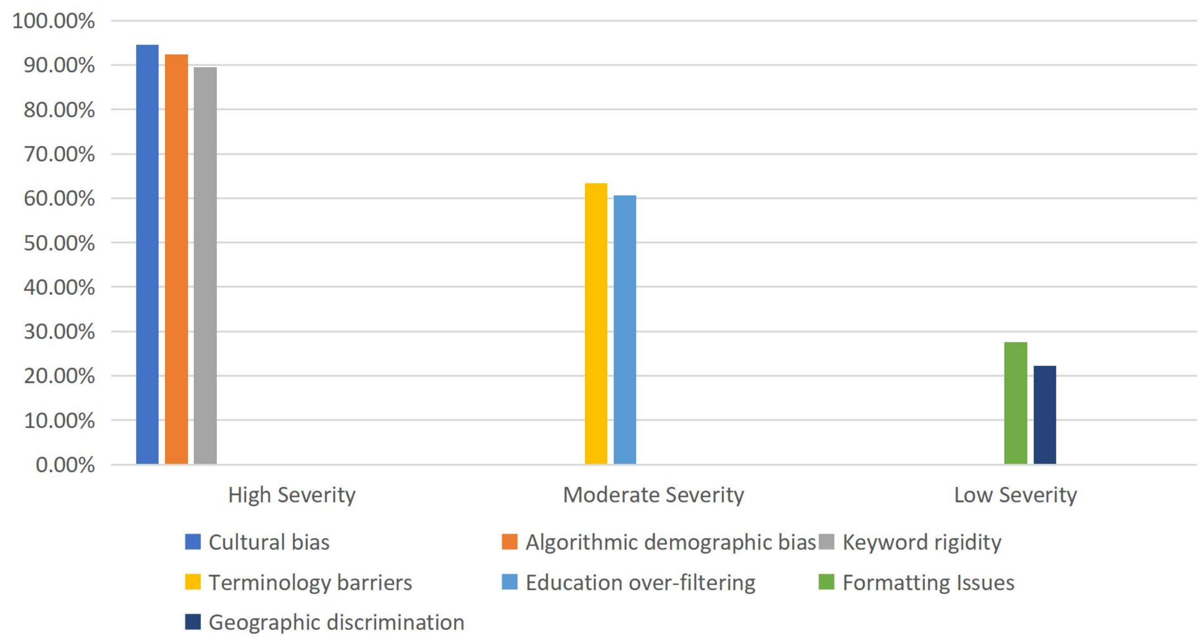

Figure 4.5 Bar Chart Showing bias severity

4.5. Summary of Key findings

Three specialized analyses revealed leading causes:

1. Cultural bias in language processing (11.9%) and educational over-filtering (10.6%) lead false rejection, with relatively even distribution across 12 causes indicating multifaceted problems requiring comprehensive solutions..

2. Over-Filtering Impact: Affects 70.4% of ATS users (52% of all organizations), with 100% implementing mitigations but 0% achieving elimination, establishing over-filtering as a persistent structural feature rather than a correctable implementation flaw.

3. Bias Severity: High-severity biases (26.3%) requiring algorithmic reengineering show the most resistance to remediation despite intensive intervention, indicating fundamental design limitations in current ATS architecture.

These findings establish false rejection and over-filtering as systematic challenges embedded in ATS technology, affecting fairness, effectiveness, and diversity outcomes across organizational and industry contexts.

CHAPTER FIVE

SUMMARY, RECOMMENDATIONS AND CONCLUSION

5.0. Summary

This study set out to empirically investigate false rejection and over-filtering in Applicant Tracking Systems. The analysis of data from 443 ATS-adopting organizations yielded several key findings:

1. ATS adoption is widespread (73.8%), and bias is a default condition within it, affecting 70.4% of systems and compromising candidate selection in over half of all organizations studied.
2. False rejection is not monolithic. The primary causes are socio-linguistic (cultural bias at 11.9%) and credential-based (educational over-filtering at 10.6%), followed by a range of technical and algorithmic factors.
3. Over-filtering patterns vary by industry, with sectors like Finance and Insurance favoring credential bias, while Healthcare and Education struggle with cultural bias. This indicates ATS often reinforces existing industry homogeneity.
4. A critical finding is the universal failure of mitigation measures; 100% of biased organizations attempted remediation, yet bias persisted, highlighting the depth of the challenge.

5.1. Recommendations

Based on findings from the study, the following recommendations are proposed:

1. For ATS Developers and Vendors:

- Prioritize the development and integration of advanced, culturally competent Natural Language Processing (NLP) engines to mitigate cultural and linguistic bias.
- Implement transparent, auditable algorithms that allow for bias detection and facilitate fundamental reengineering, not just surface-level parameter tuning.
- Move beyond keyword matching toward semantic analysis and skills-based parsing to recognize equivalent competencies and non-traditional career paths.

2. For HR Professionals and Organizations:

- Treat ATS as a supportive tool, not a definitive arbiter. Reinstate meaningful human oversight at critical screening stages to catch algorithmic errors.
- Conduct regular, mandatory bias audits of their ATS outputs to identify and understand their specific over-filtering patterns.

3. For Policymakers and Regulators:

- Develop and enforce standards for algorithmic transparency and fairness in hiring technologies, similar to existing anti-discrimination laws.
- Fund independent research into bias-resistant algorithmic frameworks and promote the creation of open-source, fair-by-design ATS tools for broader industry adoption.

5.2. Conclusion

The study concludes that false rejection and over-filtering are not mere implementation flaws but are systematic, embedded features of contemporary ATS technology. The persistence of bias, particularly the high-severity socio-cultural and demographic types that resist current mitigation efforts, points to a fundamental limitation in the core design and architecture of these systems. The optimistic claims in some literature about technical solutions are not yet borne out in practice. Therefore, achieving fair candidate selection requires moving beyond procedural adjustments toward a fundamental redesign of ATS algorithms with fairness as a core principle, not an afterthought.

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APPENDIX

1. Overall ATS Adoption rate

```
FREQUENCIES VARIABLES=ATS_Adoption
  /PIECHART FREQ
  /ORDER=ANALYSIS.



USE ALL.
COMPUTE filter_$=(ATS_Adoption = "1").
VARIABLE LABELS filter_$ 'ATS_Adoption = "1" (FILTER)'.
VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
FORMATS filter_$ (f1.0).
FILTER BY filter_$.
EXECUTE.
USE ALL.
COMPUTE filter_$=(ATS_Adoption = "1").
VARIABLE LABELS filter_$ 'ATS_Adoption = "1" (FILTER)'.
VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
FORMATS filter_$ (f1.0).
FILTER BY filter_$.
EXECUTE.
FREQUENCIES VARIABLES=Sector
  /PIECHART FREQ
  /ORDER=ANALYSIS.
```

2. Leading Causes of False Rejection

```
SAVE
OUTFILE='C:\Users\Windows\AppData\Local\Microsoft\Windows\INet
Cache\IE\F7RPG616\ATS Latest '+
```

```
    'Dataset.sav'
  /COMPRESSED.
USE ALL.
COMPUTE filter_$=(ATS_Adoption = "Yes").
VARIABLE LABELS filter_$ 'ATS_Adoption = "Yes" (FILTER)'.
VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
FORMATS filter_$ (f1.0).
FILTER BY filter_$.
EXECUTE.
FREQUENCIES VARIABLES=Bias_Cause
  /BARCHART FREQ
  /ORDER=ANALYSIS.
```