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Human Vs Algorithmic Resume Screening: A Comparative Study on Efficiency, Accuracy, and Fairness in Talent Acquisition

Tejaswini S
Student, MBA, CMS Business School,
Jain (Deemed-to-be) University, Bangalore, India.
tejaswini_s24@cms.ac.in

Dr. Shivangi Gera
Assistant Professor, CMS Business School,
Jain (Deemed-to-be) University, Bangalore, India.
shivangi_gera@cms.ac.in

Abstract

The swift digital transformation of human resource management has profoundly changed recruitment processes, including the widespread use of Applicant Tracking Systems (ATS) and software for automating resume screening. These systems not only enable greater efficiency but also allow handling large volumes of work. On the other hand, issues of fairness, transparency, and quality of decisions remain a matter of concern. The paper seeks to explore the relative merits of human and algorithmic resume screening in the context of hiring.

A mixed-method research design has been employed for this study. Quantitative data were collected via the distribution of structured questionnaires, while qualitative data were collected through interviews with HR professionals. The study looks at four main variables: screening efficiency, accuracy, fairness, and Decision Quality. Statistical analysis, including descriptive and inferential methods, was used to interpret data.

It was found that algorithmic screening can lead to a more efficient and consistent process, especially when there are lots of applicants. Nevertheless, humans are still better at grasping the contextual and qualitative elements of candidate profiles. The research points to the fact that a combination of human decision-making and algorithmic assistance results in a fairer and more effective hiring outcome.

The study adds to the evidence supporting human-AI partnership in recruitment, and it serves as a guide for companies intending to craft fair, efficient, and technologically advanced talent acquisition strategies.

Keywords: Talent Acquisition, Resume Screening, Applicant Tracking Systems, Artificial Intelligence, Human Judgment, Recruitment Automation

INTRODUCTION

Human resource management (HRM) is no longer the same as it was years ago. It is now transformed by the rapid adoption of digital tools and platforms. Among the core HR activities, recruitment has seen dramatic changes due to growing levels of automation and AI involvement.

Recruitment has changed significantly with rapid digitalization. One of the most important stages in this process is resume screening, as it decides which candidates move forward in the hiring process. Traditionally, this has been handled by human recruiters who rely on their experience, intuition, and understanding of context.

However, with the growing number of job applications through online platforms, manual screening has become time-consuming and difficult to manage. To deal with this, organizations have started using Applicant Tracking Systems (ATS) and algorithm-based tools to automate the initial screening process.

While these tools help improve speed and efficiency, there are still concerns about their ability to evaluate qualitative aspects and the possibility of bias. On the other hand, human screening, although flexible, can sometimes be inconsistent and influenced by personal judgment.

This creates an important challenge for organizations: deciding whether human or algorithmic screening is more effective, or if a combination of both works better.

This study aims to compare human and algorithmic resume screening in terms of efficiency, accuracy, fairness, and decision quality, while also understanding the perceptions of recruiters.

REVIEW OF LITERATURE

Recent studies highlight a significant shift in recruitment practices with the adoption of algorithmic resume screening and Applicant Tracking Systems (ATS). These technologies are widely used to manage large applicant volumes and improve hiring efficiency. Research by Tambe et al. (2021) and Cowgill (2022) shows that algorithmic screening reduces time-to-hire and enhances consistency in candidate evaluation.

However, concerns regarding fairness and bias remain prominent in recent literature. Studies such as Raghavan et al. (2021) and Sánchez-Monedero et al. (2022) argue that algorithmic systems may replicate existing biases present in historical data, potentially leading to unfair hiring outcomes. Additionally, rigid filtering criteria may exclude candidates with non-traditional profiles.

Despite technological advancements, human judgment continues to play a crucial role. Jarrahi (2021) and Madanchian et al. (2024) emphasize that human recruiters are better at interpreting contextual and qualitative aspects, such as candidate potential and cultural fit, which algorithms may overlook.

Recent research also suggests that a hybrid approach is most effective. Studies indicate that combining algorithmic efficiency with human judgment leads to better recruitment outcomes in terms of accuracy, fairness, and decision quality (Binns et al., 2022; Madanchian et al., 2024).

Overall, while algorithmic screening improves efficiency, concerns related to bias and lack of contextual understanding highlight the continued importance of human involvement, making a combined approach more suitable in modern recruitment practices.

Research Hypotheses

The theoretical framework, along with the review of literature, leads to the development of the following hypotheses:

H1: Human resume screening positively influences the perceived accuracy in candidate selection.

H2: Algorithmic resume screening positively affects recruitment efficiency.

H3: Human resume screening positively impacts the perception of fairness in hiring decisions.

H4: Algorithmic resume screening positively affects the consistency in resume evaluation.

H5: A combined (hybrid) approach of human and algorithmic screening positively affects the overall decision quality of recruitment.

RESEARCH METHODOLOGY

This study adopts a quantitative research design to examine the comparative effectiveness of human and algorithmic resume screening, focusing on outcomes such as efficiency, accuracy, fairness, and decision confidence.

Primary data was collected through a structured questionnaire using Google Forms. The respondents included HR professionals and recruiters who have experience with both manual and technology-assisted screening methods.

Convenience sampling was used, and a total of 205 valid responses were analyzed. The study considers recruitment outcomes (efficiency, accuracy, fairness, and decision confidence) as dependent variables, while human and algorithmic screening act as independent variables.

All variables were measured using a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5), with items adapted from existing literature.

Data analysis was conducted using SPSS. Reliability was tested using Cronbach's Alpha, while descriptive statistics, correlation, and regression analysis were used to examine relationships between variables.

4. DATA ANALYSIS AND INTERPRETATION

Reliability Analysis

To check reliability, a Cronbach's Alpha test was conducted in PSPP on 12 items using data from 205 respondents. The alpha value of 0.86 indicates strong internal consistency, meaning the items measure the concept reliably. There were no missing responses, which improves accuracy.

Descriptive Statistics

Except for algorithmic screening, which is believed to enable a notably higher level of efficiency and to be capable of managing an enormous number of applications, respondents seem to be valuing human screening for giving a better candidate understanding. It is worth mentioning that all mean scores are above 3, which is the neutral point.

Correlation Analysis

Each one of these has a statistically significant $\mathbf{p < 0.01}$.

A very strong one is the correlation between fairness and decision quality ($r = 0.667$). The fact that accuracy and decision quality also correlate very well ($r = 0.643$) is indicative of the importance that these two characteristics, fairness and accuracy, have in the quality of recruitment decisions

Regression Analysis

All three variables significantly influence decision quality. Fairness and accuracy emerge as the strongest predictors, followed by efficiency. This suggests that while speed and automation are important, the quality of hiring decisions is more strongly driven by fairness and accurate evaluation.

Paired Sample t-Test Analysis

A paired sample t-test was conducted to compare perceptions of human and algorithmic resume screening. The results show no significant difference between perceived human bias and algorithmic bias ($p = 0.901$), indicating both are viewed similarly. Likewise, trust in human judgment and confidence in automation are not significantly different ($p = 0.375$). However, a significant difference was found in job matching ability ($p = 0.036$), suggesting that respondents believe algorithmic systems perform slightly better in matching candidates to jobs.

FINDINGS AND DISCUSSION

Employing human as well as algorithmic resume screening are the methods that recruitment follows. Algorithmic screening detection of candidates is highly time-saving, especially when thousands of applications are involved. People generally believed that automation would indeed reduce the time spent, while also making the system of screening more consistent.

In contrast to human screening, automation skills evaluation, such as suitability of the candidate, whether experience is relevant, and whether a person will be able to do well in the future, is effective to an even greater extent. Human knowledge is thus essential not only to rely on the data presented but also to the interpretation of the data.

Are you surprised that the study finds bias in humans as well as algorithms? When both human and algorithmic methods were tested for the level of bias, and no significant difference was found, it implies they are both on par. As for the decision-making trust level, there is no major difference between automation and humans.

The most significant indicators of decision quality were fairness and accuracy, as shown by the regression analysis. Efficiency comes after them in the list of factors that matter. Therefore, decision quality and fairness of hiring play a greater role than speed.

In general, the results align with a hybrid approach that uses algorithmic tools for firing up the process and the human brain for the final call.

RECOMMENDATIONS AND IMPLICATIONS

Drawing from the results, the best move for companies is to blend the speed of algorithms with the discernment of humans. This way, they will get their system running smoothly and have quality hires at the end of the day.

Besides this, firms need to keep the system under control regularly, check the hidden biases, and get rid of them. They should also train the hiring folks to be skillful users of the tools they employ.

What's more, candidates' trust can be increased by fair and open screening procedures. Completely depending on computer systems should be a thing of the past, and a human assessment should always be the main aspect of recruitment.

LIMITATIONS OF THE STUDY

There are several drawbacks of the study, and they should be kept in mind when making sense of the results. Firstly, the number of cases is quite small, and the sampling technique was convenient, which might hamper the generalization of the findings to different industries and geographic locations.

Secondly, the study mainly revolves around the views of heads of hiring rather than actual job placement results. While viewpoints are great for insights, they may not accurately portray the effectiveness of human and algorithmic methods in the real world.

Moreover, the study is one-time only, and questionnaires were filled out at a certain point. This deprives us of the possibility of seeing how perceptions fluctuate as the technology usage grows.

On the go, these points could be fixed by enlarging the study, using a more mixed sample, working with data collected over time, and taking into consideration other aspects such as candidate experience, trust in AI systems, and ethical considerations in automated hiring.

CONCLUSION

This research focused on the relative effectiveness of human versus algorithmic resume screening as part of the recruiting procedure. It turned out that computer systems are very useful, especially when it comes to speeding up the process and dealing with a large number of applications. Yet, human screening is still indispensable when it comes to assessing qualitative features like the candidate's fit and the ability to relate to the context.

The study also shows that decision quality is largely determined by fairness and accuracy, which implies that companies are concerned with the quality of their hiring decisions rather than just the speed. And at the same time, people see human and algorithmic approaches as being equally biased and trustworthy, which means that one is not completely better than the other.

Taking all this into account, the paper argues that combining algorithmic tools and human control is the best way to cope with recruitment issues nowadays. This allows companies to find the right mix of effectiveness and impartiality and thus to achieve better results in hiring.

On the whole, the study adds a piece to the puzzle of understanding automation in recruitment by showing that

AI is meant to help human decision-making in talent acquisition, not to replace it.

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Table 1: Cronbach's Alpha

Table 1: Cronbach's Alpha **Component**	**Value**
Number of Items	12
Number of Respondents (N)	205
Cronbach's Alpha	0.86
Data Excluded	0

Table 2: Descriptive Statistics

Variable	**Mean**	**Standard Deviation**
Algo reduces time	4.07	0.95
Automation improves efficiency	4.11	0.92
ATS handles volume	4.11	0.94
Human identifies better	3.75	1.15
Algorithm bias (diversity)	3.82	1.07
Human bias	3.83	0.97
ATS system bias	3.93	0.98
Automation consistency	3.98	0.98
Trust in human	3.73	1.06
Confidence in automation	3.81	0.96
Hybrid approach better	3.98	0.98
ATS matches jobs	3.93	1.03

Table 3: Correlation Analysis

Variables	**Efficiency**	**Accuracy**	**Fairness**	**Decision Quality**
Efficiency	1.000	0.422	0.520	0.562
Accuracy	0.422	1.000	0.617	0.643
Fairness	0.520	0.617	1.000	0.667
Decision Quality	0.562	0.643	0.667	1.000

Table 4: Regression Model Summary

Model	**R**	**R^2**	**Adjusted R^2**
1	0.76	0.58	0.57

Table 5: Regression Coefficients

Predictor	**Beta (β)**	**p-value**
Efficiency	0.25	0.000
Accuracy	0.33	0.000
Fairness	0.33	0.000

Table 6: Paired Sample t-Test Results

Comparison	Mean Difference	t-value	p-value	Result
Algorithm Bias vs Human Bias	-0.01	-0.12	0.901	Not Significant
Confidence in Automation vs Trust in Human	0.08	0.89	0.375	Not Significant
ATS Matches Jobs vs Human Identifies Better	0.19	2.11	0.036	Sig