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Analyzing False-Reject Costs in AI Hiring Systems and Their Impact on Talent Yield

Dr. Shetty Deepa Thangam Geeta [1], Evanglin Jain J[2], Kanish Jeya Varathan J [3], Nithish Kumar L[4]
[1]Assistant Professor, School of Management Studies,
Sathyabama Institute of Science and Technology, Chennai, India
Orc Id - 0000-0003-4645-0202
Email ID : drshettydeepa@gmail.com
[2]II MBA, Student, School of Management Studies,Sathyabama Institute of Science and Technology, Chennai, India
Email ID : evanglinjain@gmail.com
[3]II MBA, Student, School of Management Studies,Sathyabama Institute of Science and Technology, Chennai, India
Email ID : Kanishj799@gmail.com
[4]II MBA, Student, School of Management Studies,Sathyabama Institute of Science and Technology, Chennai, India
Email ID : lnithishkumar2420@gmail.com

ABSTRACT
Artificial intelligence (AI) has become an important aspect of recruitment with automated decision-making systems operating to screen, rank and select candidates using prediction algorithms. In this respect, Type II errors (also referred to as 'false reject errors') happen when eligible job applicants are denied an opportunity to work in an organisation. Although AI systems can be specifically developed to be efficient and accurate, little is known about the cost of such false negatives. This paper is conceptual and analytical as it uses the Statistical Decision Theory and Signal Detection Theory to investigate the cost of false-reject errors. These models bring out the fundamental trade-off between accuracy and recall in classification systems, in which high rates of accuracy would result in the high possibility that good candidates are excluded. The results show that this type of optimisation favouritism is a serious threat defrauding talent output and organisational functionality. In addition, once training data trained through algorithms causes bias, it worsens the risks of exclusion. The research concludes that to reduce the occurrence of the hidden losses, equitable hiring, balanced model calibration, and human oversight are necessary as governance mechanisms...
Keywords: AI recruitment, false reject, talent yield, algorithmic bias, decision theory, predictive hiring, HR analytics

INTRODUCTION:

Artificial intelligence introduction in talent management has transformed the area of talent acquisition by supporting automated screening of resumes, scoring of candidates and decision support. Companies are turning to machine learning algorithms to aid efficiency, minimise hiring times, and make a hiring process more predictive (Van Esch et al., 2021). With the introduction of such systems, however, there are new sources of type of decision error, especially false rejects where the qualified candidates are sieved incorrectly during the initial screening of candidates.

A significant but not understudied issue in AI based hiring systems is false-reject errors. Organisations usually strive to reduce false positives, as this way they cannot miss recruiting an unsuitable candidate, but in the process, it increases the chances of missing high-potential candidates (Pessach and Shmueli, 2022). This leaves a large research void on the issue of the unnoticed economic and strategic costs of lost talent.

1. THEORETICAL FOUNDATIONS

2.1 Statistical Decision Theory

The Statistical Decision Theory gives a conceptual basis for the interpretation of classification error by AI systems. During the process of recruitment algorithms, decisions are made in uncertainty; that is, candidates are defined as appropriate or inappropriate based on probabilistic models. There are two kinds of error, which are false positives and false negatives. The importance of cost-sensitive decision-making is that such errors need not have an equal impact. False negativity (full of qualified candidates, which is more likely to occur in the hiring context) can be more expensive in the long run than false positivity (Raghavan *et al.*, 2020).

2.2 Signal Detection Theory

Signal Detection Theory (SDT) describes the choice made when there exists uncertainty and differentiates between signal (qualified candidates) and noise (unqualified candidates). The theory brings in the theory of a decision threshold, which represents the filtering of candidates with rigidness.

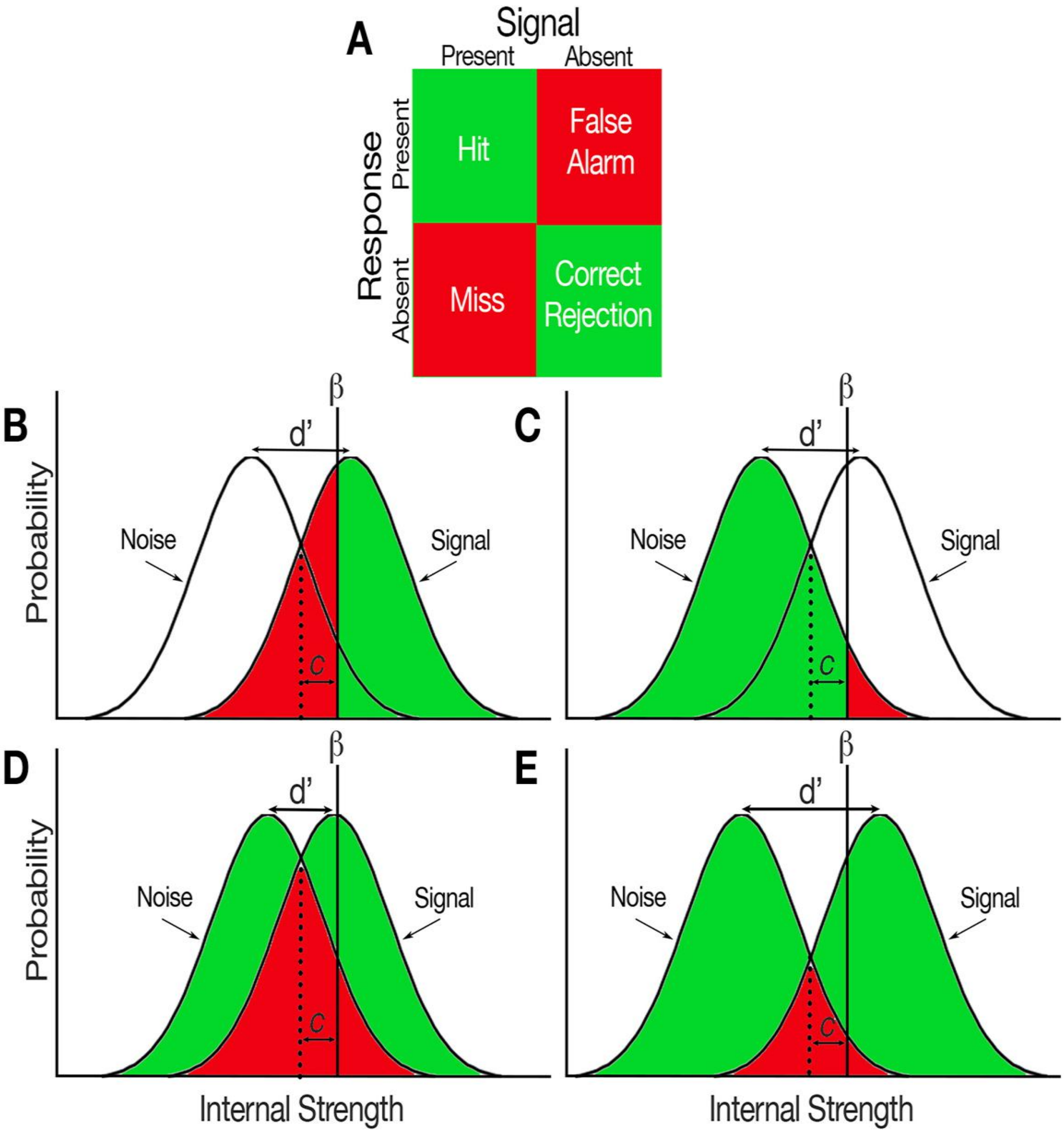

Figure 1: Signal Detection Theory (SDT)

(Source: Liem *et al.*, 2021)

An increase in threshold enhances accuracy but decreases the recall, increasing false rejection. This is especially an important trade-off with AI hiring systems, where too conservative thresholds will filter out potentially valuable applicants (Liem *et al.*, 2021).

2.3 Human Capital Theory

The Human Capital Theory literally treats employees as an asset that adds to the organisational productivity as well as its competitive advantage. In this sense, losing qualified individuals will be a loss of potential economic value. Employees who perform well will not only help it perform efficiently but also become innovative and develop over time. False-reject errors, thus, come with opportunity costs that do not just end with hiring decisions here and now (Chamorro-Premuzic *et al.*, 2021).

2. AI HIRING SYSTEM ARCHITECTURE

3.1 Data Sources and Feature Engineering

The AI systems of employment are based on various data sources: the resumes, psychometric tests, and behaviour traces, such as internet usage and communication behaviour. This raw data is converted into a structured form in the form of variables which can be processed by algorithms, which is what feature engineering accomplishes. Nonetheless, model predictions can be biased or incomplete because previous hiring patterns are accurate depictions of the current disparities in the world (Mehrabi *et al.*, 2021).

3.2 Algorithmic Models

Applications of natural language processing (NLP) in recruitment systems are predominantly utilised to examine trader applications and machine learning algorithms to estimate the aptness of candidates. In these models, the scores are given out of the pattern learnt and the candidate ranked. Although effective, they rely on the quality of training data and model assumptions, which may affect the error rates as well as decision outcomes.

3.3 Bias and Error Entry Points

Bias may be introduced into the AI systems in various ways, such as biased training data, improperly selected features, or more indirectly as a proxy variable to indirectly precode some sensitive outward trait. Those biases make the systematic exclusion of specific groups of candidates more likely, which amplifies the false-reject error and supports the preexisting inequalities (Sanchez-Monedero *et al.*, 2020).

3. FALSE-REJECT COST ANALYSIS FRAMEWORK

4.1 Classification of Costs

There are several types of costs formed as a result of false-reject errors. Direct costs come in due to the inability to recruit qualified candidates, which results in lengthy vacancies and higher recruitment costs. The lost productivity is classified as an indirect cost because organisations fail to have high-performing people who can help improve operational efficiency. Moreover, opportunity costs are manifested as low levels of innovativity and a lack of competitive edge. Also critical are the diversity-related expenses, because biased algorithms can proportionately shut out under-represented populations, impacting the inclusion initiatives (Köchling and Wehner, 2020). These compound costs both point to the fact that false rejects are not just statistical mistakes but strategic risks with long-term consequences.

4.2 Mathematical Cost Model

The cost of false rejects is expected to be worked out with the help of a probabilistic loss function:

Expected Loss = P(False Reject) × Cost per Candidate

This model shows that the losses that can be total are a product of both the likelihood of making an error and the economic value of the lost candidate. The cost per reject is much greater in high-skill positions where the individual contribution is considerable. Thus, the chance of losses in the case of the false rejection can be potentially excessively large because a small deviation can result in large losses, and cost-sensitive model calibration is required (Raghavan *et al.*, 2020).

4.3 Talent Yield Model

The talent yield is the ratio of the number of suitable candidates that is recruited among the number of applicants. It is well associated with recall in the classification models. The stricter the decision thresholds, the lower the rate of recall which causes reduced talent yield. Such a shortening does not only decrease the number of candidates applying, but also influences the quality of those candidates, as people of potential can be disqualified at an early stage (Pessach and Shmueli, 2022). In this way, maximization of precision at the expense of recall leads to reduced effectiveness of recruitment.

4. IMPACT ON TALENT YIELD AND ORGANISATIONAL OUTCOMES

5.1 Talent Pool Compression

Denied talent pool false-reject error minimises the size of the pool of potential talent before they progress to subsequent levels of selection. This squeegee diminishes variety and narrows the diversity of skills that organisations have. Since the AI systems only eliminate the unqualified candidates through pre-specified conditions and filtering, the possibilities of acquiring talent are restricted when the talent is unusual to AI, which is quite unconventional yet talented (Van Esch *et al.*, 2021).

5.2 Innovation and Productivity Loss

The organisational innovation and productivity are direct products of the exclusion of high-potential candidates. Problem-solving and creativity require different views and distinct skill sets. In cases where the AI systems have been engineered to automatically eliminate such candidates, the organisations are denied a chance at innovation and long-term expansion. This corresponds to the human capital theory, which highlights the importance of talented workers as the force of competitive advantage (Chamorro-Premuzic *et al.*, 2021).

5.3 Strategic and Employer Branding Effects

Lots of false dismissals can have a deteriorating effect on employer branding since applicants view hiring as a murky process. Such perception lowers the confidence of the applicants and does not motivate the good-quality candidates to pursue the application in the future. Furthermore, the reputational loss can also occur when the algorithmic bias can be seen, which also impacts the organisational appeal (Sánchez-Monedero *et al.*, 2020).

5. OPTIMISATION AND GOVERNANCE STRATEGIES

6.1 Precision-Recall Trade-off Optimisation

The process of balancing the cost of precision and recall is crucial in reducing the cost of false rejects. Single models like the F1-score have a more detailed picture of the performance of the model since they model these two dimensions. Raising or lowering decision thresholds to attain this balance may yield better talent output without increasing false positives to a large extent (Mehrabi *et al.*, 2021).

6.2 Explainable AI (XAI) Framework

Explainable AI improves transparency by giving information on the way decisions are made. This enables organisations to determine and rectify biases within models of recruitment. XAI helps to make algorithmic processes transparent, which supports accountability and allows obtaining a better connection with fairness goals (Liem *et al.*, 2021).

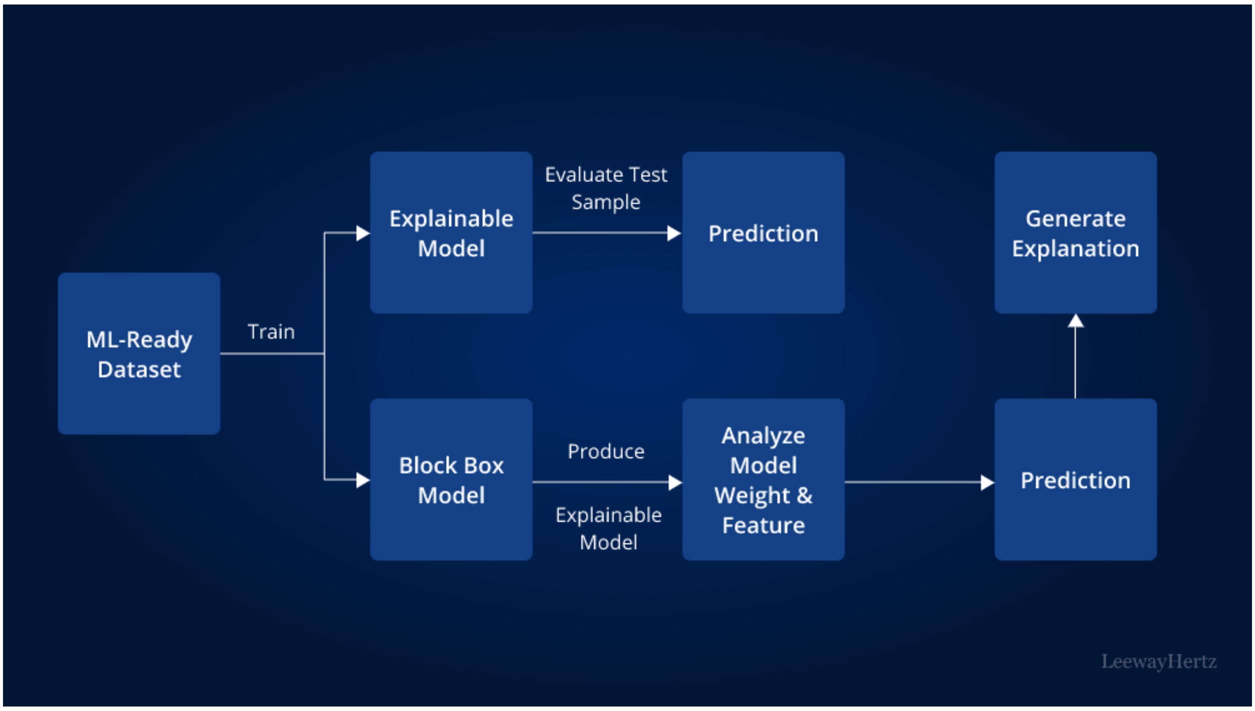

Figure 2: XAI Framework

(Source: Liem *et al.*, 2021)

6.3 Human-in-the-Loop Systems

Human judgement should be incorporated into the hiring procedures using AI, which reduces error and enhances the quality of decisions. Borderline cases can be discussed by human reviewers who will be able to give contextual information that may be missed by algorithms. This combined system will make sure that automation will not automatically confer efficiency at the expense of justice and diversity (Raghavan *et al.*, 2020).

6. CONCLUSION

False rejects in the hiring systems based on AI are an important but neglected way of organisational cost. These mistakes decrease the yield of talent, impair diversity and weaken competitiveness in the long run by eliminating qualified candidates. The research shows that these results are interconnected with the decision thresholds and optimisation strategies with precision and not the recall preference. Such a combination of theoretical models like Statistical Decision Theory and Signal Detection Theory gives more insight into these trade-offs.

In order to overcome these challenges, it is necessary to turn to balanced model calibration, introduce explainability, and introduce human control mechanisms into an organisation. These measures are able to minimise unspoken expenses as well as promote equity and effectiveness in the recruitment procedures. The next step in terms of optimising AI hiring systems should consider research that involves the optimisation of dynamic thresholds and the incorporation of fairness metrics to ensure that the talent acquisition practices become more sustainable..

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