EPH-International Journal of Business & Management Science

AI-ENABLED TALENT ACQUISITION: OPPORTUNITIES, CHALLENGES, AND ADOPTION STRATEGIES IN GUJARAT'S SERVICE INDUSTRIES

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Article History
Received: *2026-05-25*
Revised: *2026-09-29*
Accepted: *2026-10-31*
Published: *2026-11-25*

Abstract
Artificial intelligence is a chance to streamline the recruitment process, but predictive accuracy is not sufficient to guarantee transparent, reliable, and responsible hiring choices. This paper invents an interpretable machine learning model into recruitment decision support and analyzes the predictive accuracy, explanatory significance, and strength. Statistical testing, leakage-aware preprocessing, and three classifiers were used to analyze a publicly available Kaggle dataset of 1500 synthetic candidate records, which included Logistic Regression, Random Forest, and XGBoost. Classification measures, probability calibration, permutation features importance, and simulated missing-data noise were used to evaluate models. XGBoost was chosen with the help of training-only cross-validation and test accuracy, F1-score and ROC-AUC were 93.00, 87.57, and 0.9311 respectively. The most significant predictor was recruitment strategy, which had a permutation importance of 0.2414 in the decrease of ROC-AUC. The accuracy decreased to 88.00 when the percentage of data below 10% missingness was additionally missing, showing that the accuracy depends on the quality of the data. These results suggest that discrimination performance should not be used solely to select a model and interpretability and resilience are significant qualities that should be taken into account. The research provides a cohesive analytical basis of human-managed recruitment choices. However, there is a lack of external validation and synthetic data, future research should include real hiring scenarios, algorithmic fairness and organizational performance. The responsibility of human supervision is needed in terms of effective operational adoption.

Key Words: *Artificial Intelligence, Recruitment Decision Support, Machine Learning, Explainable AI, Talent Acquisition*

Vol. 12 Issue 7s (November, 2026)
ISSN: 2208-2190 Pages- 70-82
DOI: https://doi.org/10.69023/rs8bky20

1. Introduction

Artificial intelligence (AI) is a revolutionary technology in human resource management (HRM), where organizations can automate human resource recruitment processes, enhance screening of candidates, and enhance evidence-based human resource decisions. Traditional hiring methods tend to be manual, based on evaluation of resumes, subjective and time-consuming selection processes that may decrease the efficiency of operations and create discrepancies in the hiring process. Recruitment systems supported by AI can provide the opportunity to systematize the data of the applicants, find the necessary features of candidates and enhance the quality of the selection of the personnel. Nevertheless, to be successfully implemented, it is important to pay close attention to the data quality, transparency of the algorithm, organizational preparedness, and human control (Tambe et al., 2019). The recent advances in technology have also extended the use of machine learning, predictive analytics, and intelligent automation to the HRM functions, which has resulted in the opportunity to incorporate computational intelligence into the strategic workforce planning and organizational decision-making (Vrontis et al., 2022).

The introduction of AI-based talent acquisition is especially applicable to companies that want to enhance the effectiveness of the recruitment process and, at the same time, retain the quality of the selection results. Recent research indicates that technological compatibility, perceived usefulness, organizational resources, and managerial support are factors that affect the implementation of an AI-based recruitment system (Pillai and Sivathanu, 2020). The degree of AI integration in employee selection processes is also influenced by contextual factors, such as organizational culture, recruitment policies, technological infrastructure, and stakeholder acceptance (Pan et al., 2022). Therefore, the idea of recruitment automation must not be perceived solely as a technological intervention but rather as a managerial decision-making effort that needs to balance the opportunities of technology with the business goals. In order to create sustainable value through intelligent uses of HRM, appropriate AI capabilities such as data management, analytical capabilities and institutional preparedness must be formed (Chowdhury et al., 2023). Successful implementation also necessitates the coordinated modifications in the organizational practices, staff skills, and technology management to make sure that AI-generated suggestions can add value to recruitment choices (Jatobá et al., 2023).

Despite these opportunities, traditional recruitment systems are still dealing with issues related to a lack of consistency in candidate assessment, the lack of analytical ability, a lengthy screening process, and possible selection bias. Despite the potential to enhance the efficiency of the processing and aid objective evaluation, AI-based methods introduce the issue of interpretability, accountability, discriminatory decisions, and overreliance on automated suggestions (Ore & Sposato, 2022). In addition, predictive accuracy does not determine the feasibility of an intelligent recruitment system. The decision support in recruitment involves the need to have models that will determine the relevant applicant characteristics, make credible predictions of hiring and provide interpretable evidence to HR managers. A combination of machine learning with mathematical and prescriptive analysis can strengthen the process of recruiting personnel by connecting predictive data with the decision to proceed with the recruitment process (Pessach et al., 2020). Nevertheless, how to transform the outcomes of algorithms into sensible, responsible and actionable recommendations is one of the questions that are yet to be answered.

Ethics also makes the use of AI in the recruitment process more complex, especially in cases where automated tests affect employment. The potential to reproduce biases in historical data can be in algorithmic decisions, whereas a lack of transparency can erode applicant trust and managerial responsibility. Recent studies underline that technological advancements to improved recruitment systems should be accompanied by fairness, explainability, protection of privacy, and responsible governance (Mori et al., 2025). Empirically based methods that integrate predictive performance and practical recruitment use and organizational decision-support applications are also found to be in need (Dadaboyev et al., 2025). Even though the literature confirms the increasing relevance of AI in the selection of employees, additional efforts are needed to determine how attributes related to recruitment can be systematized and converted into comprehensible hiring suggestions. Recent research syntheses also emphasize the need to consider the capabilities, constraints, and implications of AI-aided recruitment instead of assessing the automation entirely based on technical performance (González-Morales et al., 2026).

It is against this backdrop that the current paper examines an AI-based recruitment decision support model based on structured data with 1,500 artificial candidate profiles, ten predictors, and a dichotomous hiring decision. The machine-learning hiring prediction, the comparative model analysis, and the feature-importance analysis to understand the features involved in hiring decisions are the predictive model. The idea of AI adoption proposed is conceptually related to predictive analytics and managerial interpretation and responsible recruitment practices. The experiment is based on computation assessment on the existing dataset as opposed to real organization implementation. It is constrained by the artificiality of the records, variables that are

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ISSN: 2208-2190 Pages- 70-82
DOI: https://doi.org/10.69023/rs8bky20

measured in the dataset and lack of prospective validation of it by real recruitment decisions. Findings then should then be understood to be indicators of analytical possibility and not demonstrate betterment of the quality of hiring, equality and company functioning in real world.

The investigation of managerial implication of AI-enabled talent acquisition in Gujarat can be applied to the service industries as its potential application environment. The decision-support model suggested will be tailored to assist the organizations to speculate on the recruitment opportunities, implementation challenges, and responsible adoption approaches. A local focus on future application and utilization of the framework, as opposed to the geographical source of the experimental data; the synthetic recruitment records fail to clarify on the applicants and firms in Gujarat.

This research is important as it combines predictive recruitment analytics with an interpretable decision-support view. The research will provide a methodological background of automated hiring predictions knowledge by contrasting the techniques of machine-learning; as well as by comparing the relative importance of candidate characteristics. It also adds to the debates on the responsible AI application as it finds a way of separating the computational forecast and the ultimate managerial choice. To this end, the research has three research objectives:

- To develop and evaluate machine-learning models for predicting hiring decisions using structured candidate characteristics and recruitment-related variables.
- To compare predictive performance and identify influential recruitment attributes through appropriate classification metrics and permutation-based feature-importance analysis.
- To propose an interpretable AI-enabled recruitment decision-support framework that connects predictive evidence with managerial hiring decisions, organizational adoption considerations, and responsible human oversight.

With these goals in mind, the research aims to add to AI-based talent acquisition, predictive HR analytics, and research on organizational decision-support, acknowledging the constraints of synthetic recruitment data and the necessity of its real-life validation.

2. Literature review

Artificial intelligence (AI) has recently become an increasing topic of research interest in the field of recruitment and personnel selection because it has the potential to improve predictive accuracy, efficiency, and evidence-based decision-making. However, in the recent literature, the barriers to algorithmic fairness, transparency, organizational acceptance, and implementation are identified as important ones. In a systematic review of automatic decision-making in the recruitment and human resource development processes, it was found that automated selection systems can reproduce pattern of discrimination when training data were founded on historical inequalities or when the attributes of the candidates are evaluated based on a biased process (Köchling and Wehner, 2020). Similar studies investigating bias reduction in algorithmic hiring pointed out the risks of commercial fairness arguments and the need to consider actual selection procedures, data properties, and institutional responsibility instead of focusing on the presumption that automated systems produce objective decisions by default (Raghavan et al., 2020).

Empirical studies have also shown that high predictive accuracy may not always ensure fair recruitment processes. The study of algorithmic video analysis in the recruitment process found the possibility of discrimination regardless of high classification accuracy, which demonstrates the importance of measuring fairness in addition to the traditional predictive indicators (Köchling et al., 2021). To mitigate these issues, an ethical decision-making approach to AI-enabled HRM was focused on transparency, responsibility, human control, and responsible organizational management. Although this is a useful tool of management, the conceptual focus of the method does not directly determine predictive performance or efficiency in the operation of recruitment classification (Bankins, 2021). A study investigating the reactions of applicants towards AI-supported recruitment, also indicated the significance of perceived fairness, the ability to prove competence, and the rise of emotion towards automated evaluation. These results suggest that organizational adoption is determined by factors besides technical effectiveness; it also requires candidate acceptance and trust (Köchling et al., 2023).

In addition to ethical and organizational issues, machine-learning methods have already been shown to be of great potential in the analysis of information related to recruitment. Studies using work-history data on applicants indicated that predictive analytics can be used to make decisions related to personnel by finding patterns related to future employee performance and turnover. However, the method of predicting employment based on past records could be sensitive to the nature of data sets, organizational environment, and the presence of valid measurements of the outcomes (Sajjadiani et al., 2019). A recent systematic review of AI, organizational knowledge and HRM also found tensions between strategic human resource capabilities and

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ISSN: 2208-2190 Pages- 70-82
DOI: https://doi.org/10.69023/rs8bky20

technological automation. Although AI has the potential to enhance the organizational intelligence and knowledge-based decision-making processes, its advantages are conditional upon the capability to combine analytical outputs with managerial skills, proper governance, and organizational goals (Úbeda-García et al., 2025).

Random Forest is one of the well-known methods of classification that provides a powerful ensemble-learning methodology including several decision trees to enhance predictive stability and support nonlinear relationships between input factors. Its benefits are flexibility, insensitivity to instability of individual trees and the possibility of determining the importance of variables. Nevertheless, the complexity of models can decrease their direct interpretability, whereas predictive accuracy also depends on the quality of training-data and the proper validation (Breiman, 2001). Another powerful method is Extreme Gradient Boosting (XGBoost) that offers sequential tree boosting, regularization, and optimization of computations. It is capable of efficiently modeling complicated interactions and obtaining high classification performance, but high sensitivity to hyperparameters and tuning needs, as well as reduced model interpretability, can make it challenging to apply to practice (Chen and Guestrin, 2016).

The techniques of interpretability have thus gained significance to translate machine-learning predictions into information that can be used in decision-making. Permutation-based feature-importance analysis is a method to assess predictor relevance by quantifying the variation in model performance in response to perturbation of the feature in question. A study that proposed a fixed permutation-importance method showed the difference between important contributions of predictors and potentially false importance estimates. However, feature-importance rankings do not imply any causal relationships and can be unstable in the case of correlated predictors (Altmann et al., 2010). More recent studies that synthesized AI application in the recruitment and selection domain using an AI taxonomy provide additional instances of AI diversity of computational methods and their possible organizational uses. Growing technical, ethical, and managerial research fragmentation, however, makes it more difficult to develop integrated recruitment decision-support frameworks (Herold and Roedenbeck, 2025).

Research Gap: The current literature offers a lot of evidence related to algorithmic fairness, applicant perceptions, organizational adoption, predictive machine-learning techniques. Nevertheless, little focus has been on incorporating classification-model comparison, interpretable feature of recruitment analysis, and managerial decision considerations into a single analytical platform. Moreover, the concept of predictive performance is often considered in isolation of practical interpretation of model outputs and responsible adoption of AI. The current research fills this gap by testing machine-learning models to predict hiring based on structured synthetic candidate data, assessing the overall impact of recruitment attributes with permutation analysis, and suggesting a conceptual AI-enabled decision-support framework. Such a combination will help to enhance the methodological relationship between recruitment forecasting and managerial interpretation but not to ignore the fact that the evaluation of synthetic-data cannot be used to determine the effectiveness or fairness in the real world.

3. Methodology

3.1. Research Design and Data Sources

This paper used a quantitative, data-driven research design that combines statistical analysis, machine learning (ML), and explainable artificial intelligence (XAI) to examine predictive power of AI-based talent acquisition systems and their possible managerial consequences to the service industries in Gujarat. The methodology was a two-complementary element that included a computational evaluation of the recruitment outcomes based on the secondary data and an offered organizational adoption evaluation based on the perceived opportunities, implementation issues, and strategic preparedness. The computational analysis used the publicly available Recruitment Dataset created by Rabie El Kharoua, which included 1,500 synthetic candidate records that had recruitment-related features and binary hiring decisions. Variables in the dataset were experience of the candidate, educational background, performance during interviews, skills tests, personality traits, and recruitment methods.

The main purpose of the analysis was to assess the ability of traditional statistical learning and ensemble-based algorithms to make accurate and consistent predictions of recorded recruitment choices. The targeted managerial application context was offered by the service industries of the state of Gujarat, especially information technology, banking, healthcare, hospitality and retail. The secondary data, however, was not reflective of actual recruitment practices in Gujarat. Thus, regional adoption was viewed as a distinct research element that needed to be genuinely evidenced by organization survey. Any computational process was done in Python with the help of Visual Studio Code and developed statistical and machine-learning packages.

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ISSN: 2208-2190 Pages- 70-82
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Consequently, the study is a computational proof of concept with a suggested Gujarat-based managerial implementation, rather than a field assessment of the adoption of AI in the state. The estimated ML performance was not based on any region-specific responses, organization-level observations or local deployment outcomes.

3.2. Data Preprocessing and Exploratory Statistical Analysis

Preprocessing of data was done to enhance consistency in analysis and reduce unnecessary modelling errors. A publicly accessible Kaggle repository of synthetically constructed candidate traits and recruiting results was used to obtain the recruitment dataset (El Kharoua, 2024). The first step was to analyze the dataset regarding missing values, multiple records, inconsistent types of data, invalid values, and possible redundant variables. Redundant records and observations with invalid outcome labels were filtered out, and candidate identification fields and possible target-leakage variables were filtered prior to the development of the models. Numerical and categorical predictors were established based on their recorded properties where the variable coding had to be reviewed to identify the continuous measurements and categorical indicators.

Numerical values that are missing were replaced with the median method of imputation, and categorical variables were handled with the help of applying proper imputation and encoding one-hot. The StandardScaler transformation was used to normalize numerical predictors. To avoid leakage of information, preprocessing parameters were not estimated on the entire dataset, but on model-training pipelines.

Exploratory data analysis consisted of frequency distributions, descriptive statistics, measures of central tendency and dispersion, and relationship between the candidates' attributes with recruitment results. The relationships between numerical features were analyzed with Spearman correlation coefficients, and the independent-samples t-tests of Welch, Mann-Whitney U test, and chi-square test were used where needed. Cohen d and Cramer V was used to quantify the level of association, and the Benjamini-Hochberg test was used to control the false discovery rate in exploratory comparisons. Statistical results were considered to be associations in the synthetic data and not cause-effect.

3.3. Machine Learning Model Development and Hyperparameter Optimization

Three aided classification algorithms were used: Logistic Regression (LR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost). The Logistic Regression was used as an interpretable linear baseline, and the other two models (Random Forest and XGBoost) were used as an ensemble-learning model that can identify nonlinear predictors and interactions among recruitment predictors.

This cleaned data was split into 80:20 stratified train-test with a fixed random seed of 42 to maintain the hiring-outcome distribution. Scikit-learn pipelines were used to preprocess and estimate models. The cross-validation was five-fold stratified and conducted on the training partition only to assess the stability of the model and aid in the selection of hyperparameters.

Hyperparameter optimization used RandomizedSearchCV, which considers the regularization parameters of Logistic Regression, tree structure and sampling parameters of Random Forest, and learning rate, tree depth, estimators, and regularization parameters of XGBoost. The F1-score was chosen as the main optimization objective since it avoids bias to either precision or recall. The model with the best cross-validation F1-score selected was retained to be further evaluated. The performance reporting was based on the held-out test partition instead of the hyperparameter selection, but its previous baseline check was identified as a methodological constraint.



Figure 1. Proposed Methodological Workflow for AI-Enabled Talent Acquisition Analysis and Adoption Strategy Development.

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3.4. Model Performance Evaluation, Explainability, and Robustness Assessment

The accuracy, precision, recall, F1-score, specificity, balanced accuracy, and area under the receiver operating characteristic curve (ROC-AUC) were used as predictive performance measures. The classification errors were represented using confusion matrices, and the probability calibration error was measured using Brier scores, log loss and reliability diagrams. The differences in training and testing performance were checked to find out possible overfitting.

The permutation feature importance was used to determine the interpretability of the model as opposed to SHAP. The algorithm was used to measure the decrease in validation ROC-AUC when individual predictors were randomly permutated and highly repeated. Approximating the average importance and variability was done by permuting 30 times which enabled the determination of the most important features in predictive performance.

The concept of robustness was studied in the context of controlled numerical perturbation and other instances of missing-values. Additional performance stability and conditional uncertainty measures were variability of cross-validation (5 times), and bootstrap resamples (500 times). In the case of documented subgroup attributes, the exploratory fairness assessments took into account the variations in positive prediction rates, true-positive rates, and false-positive rates. These diagnostics were not regarded as evidence of external validity or non-discriminatory recruitment but as internal reliability measures.

3.5. AI Adoption Assessment and Managerial Strategy Development

The organizational adoption element was designed based on five constructs that included perceived AI opportunities, implementation challenges, organizational readiness, adoption strategies, and adoption intention. A questionnaire with four five-point Likert-scale questions per construct was proposed to potential respondents in the service industries of Gujarat, namely, HR professionals and recruitment decision-makers.

Providing there are authentic survey responses, the analysis process involved descriptive statistics, construct-comparable scoring, Cronbach alpha reliability estimation, and Spearman correlation, whereas false discovery rate is modified when multiple comparisons are made. The computational workflow failed to determine the regional adoption rates and confirmed organizational relationships without primary survey evidence.

Lastly, the predictive modelling results were conceptually combined with the organizational adoption factors to create a proposed managerial framework that focused on the infrastructure preparedness, AI responsibility, human control, transparency, fairness control, and ongoing recruitment-system assessment. The resulting framework was only supposed to inform future empirical evaluation and managerial decision-making and not a model of experimentally validated adoption.

4. Results

4.1. Dataset Characteristics and Exploratory Recruitment Analysis

The data consisted of 1,500 candidate records that were synthetically generated, with ten predictors associated with the recruitment process and one binary outcome of being hired. The first screening did not find any absent values in the data, observations that were identical, and constant variables. There were 465 selected and 1,035 non-selected candidates in the hiring distribution (31.0 and 69.0 respectively). After preprocessing, 1,200 observations were chosen to be used in training and 300 to be used in testing by means of stratified random partitioning.

Table 1. Dataset Characteristics, Feature Composition, and Data Preprocessing Summary.

Characteristic	Observed Value
Total candidate records	1,500
Total variables	11
Predictor variables	10
Target variable	HiringDecision
Selected candidates	465 (31.0%)
Non-selected candidates	1,035 (69.0%)
Missing values	0
Exact duplicate records	0
Training observations	1,200 (80.0%)
Testing observations	300 (20.0%)

Descriptive analysis revealed that the mean age of the candidates was 35.15 years and the average experience in the profession was 7.69 years. The average scores in terms of interview, skill, and personality were 50.56,

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51.12 and 49.39 respectively. The average scores of professional experience and assessment of selected candidates were higher than non-selected ones.

Table 2. Descriptive Statistics and Recruitment Characteristics of Candidate Records.

Variable	Mean ± SD	Non-selected Mean	Selected Mean
Age (years)	35.15 ± 9.25	35.14	35.17
Experience (years)	7.69 ± 4.64	7.31	8.54
Distance from company	25.51 ± 14.57	25.67	25.14
Interview score	50.56 ± 28.63	47.76	56.80
Skill score	51.12 ± 29.35	47.11	60.03
Personality score	49.39 ± 29.35	46.06	56.79

The comparisons made in an exploratory analysis showed statistically significant differences in experience, interview performance, skill scores, and personality scores, post-correction to false discovery rates (adjusted $p<0.001$). Recruitment strategy had a relatively good categorical relationship with hiring outcome (Cramers V = 0.5714). There were no significant differences between hiring groups in terms of age and distance.

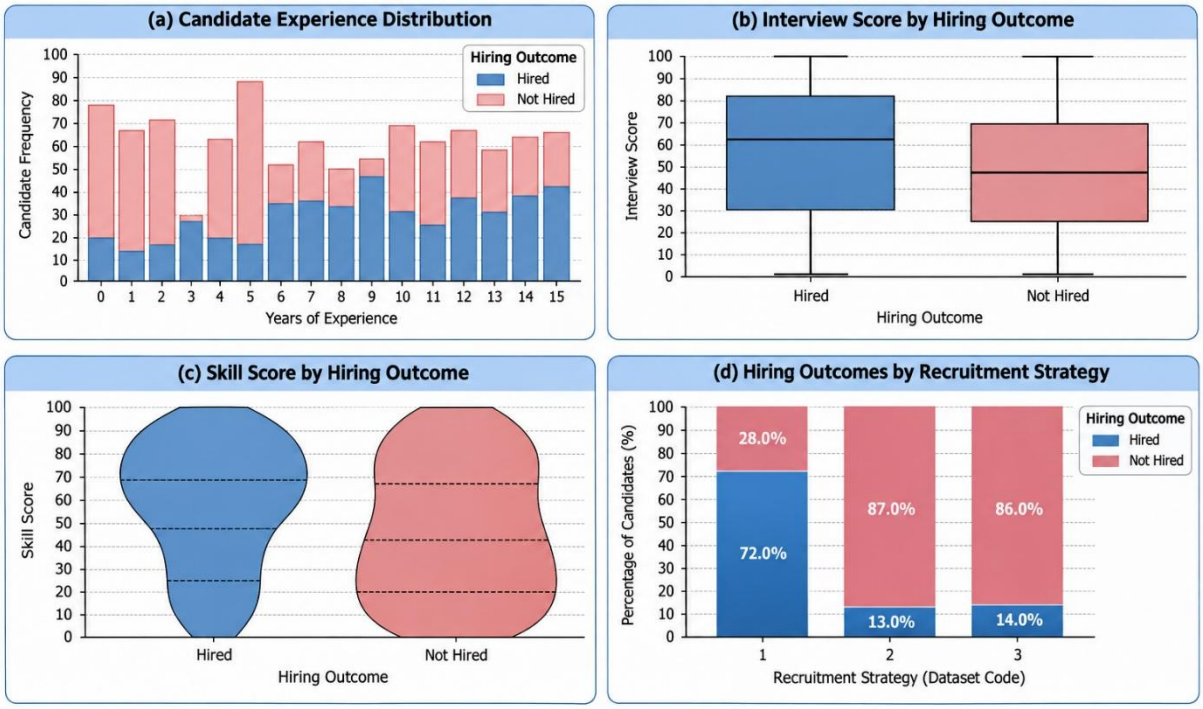

Figure 2. Distribution of Candidate Experience, Interview Scores, Skill Scores, and Recruitment Strategies Across Hiring Outcomes.

Figure 2 illustrates the distributions of recruitment characteristics and highlights differences in assessment scores across the recorded hiring categories.

4.2. Comparative Performance of Machine Learning Models

The held-out testing data was used to evaluate the predictive performance of Logistic Regression, Random Forest, and XGBoost. The classification accuracy of the three models was at least 88.0%. Both random Forest and XGBoost performed equally with 93.0% accuracy and outperformed Logistic Regression. Random Forest has the high test F1-score (0.8772) and ROC-AUC (0.9320), and XGBoost has the high precision (0.9737) and the lowest Brier score (0.0675).

Table 3. Comparative Classification Performance of Logistic Regression, Random Forest, and XGBoost Models.

Performance Metric	Logistic Regression	Random Forest	XGBoost
Accuracy (%)	88.00	93.00	93.00
Precision	0.8519	0.9615	0.9737
Recall	0.7419	0.8065	0.7957

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F1-score	0.7931	0.8772	0.8757
ROC-AUC	0.9148	0.9320	0.9311
Specificity	0.9420	0.9855	0.9903
Brier score	0.0912	0.0788	0.0675
Selected CV F1-score	0.8161	0.8301	0.8691

Despite the slightly better held-out discrimination by Random Forest, XGBoost was still chosen as the model of interest due to its highest F1-score on training only cross-validation (0.8691). Its held-out F1-score was 0.8757, which implies a widely applicable predictive performance to the reported validation processes. The chosen cross-validation estimate is still susceptible to hyperparameter-selection optimism.

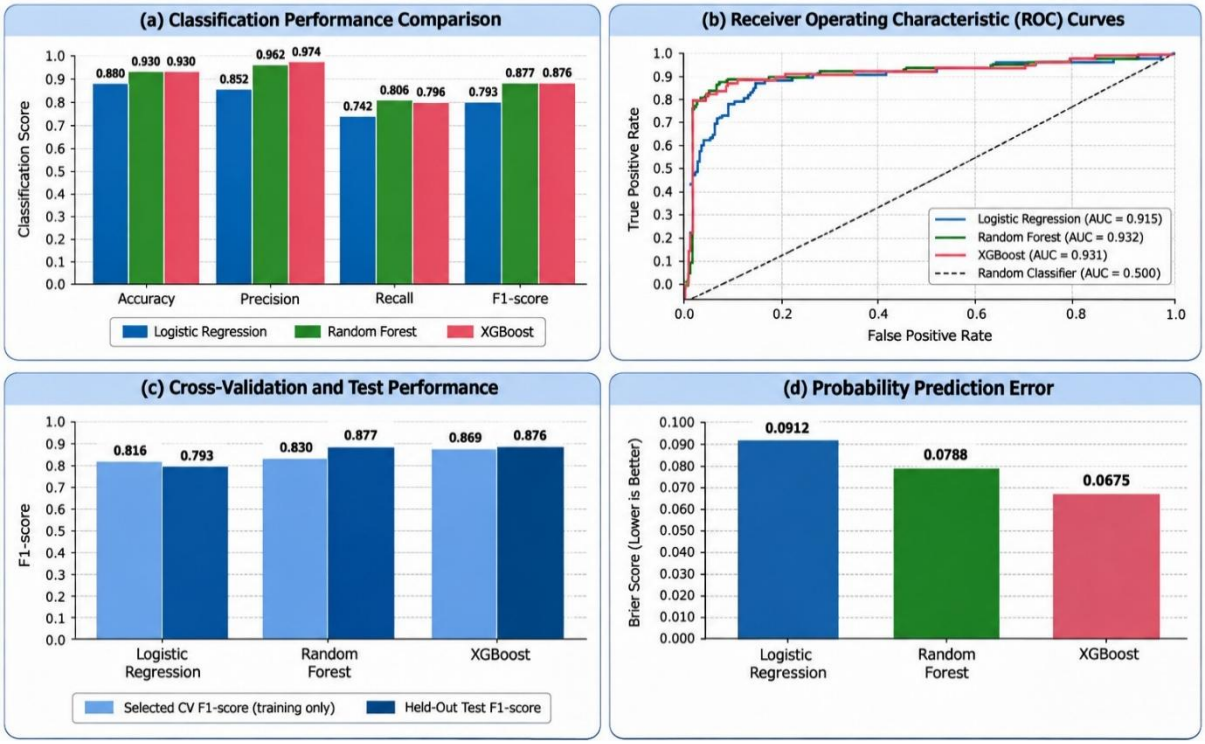

Figure 3. Comparative Classification Performance, ROC Curves, Cross-Validation Results, and Probability Prediction Errors.

Figure 3 depicts the metrics of classification, the ROC curves, cross-validation comparisons and probability prediction errors of the three optimized classifiers.

4.3. Explainable AI and Recruitment Feature Importance

The importance of the characteristics of a refitted XGBoost model that was trained on 900 training observations was permuted and tested on a separate 300-observation validation set. The model of explanation was given an F1-score of 0.8914, and ROC-AUC of 0.9376.

The most significant variable (0.2414) was RecruitmentStrategy and, therefore, it underwent the greatest decrease of predictive discrimination following random permutation. The other predictors which significantly influenced the effect were PersonalityScore (0.0514), EducationLevel (0.0504), InterviewScore (0.0449), SkillScore (0.0397) and ExperienceYears (0.0238). The age, distance, gender and number of past companies had a negligible average or even negative average.

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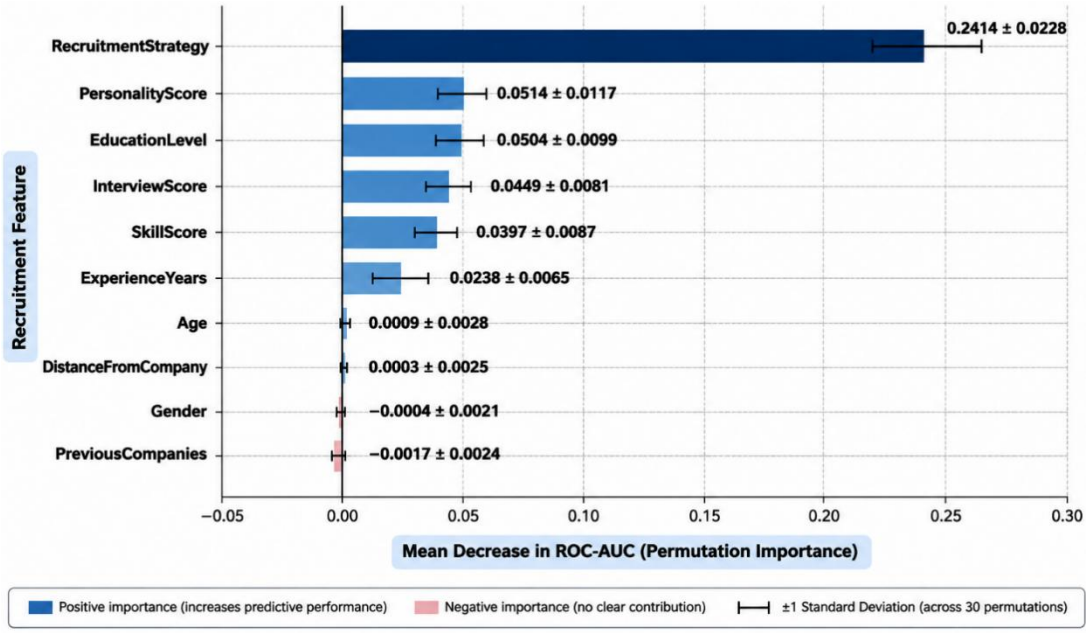

Figure 4. Permutation-Based Feature Importance of the Selected Machine Learning Model for Recruitment Outcome Prediction.

The ranking of features in terms of importance demonstrates that the classifier is mostly dependent on such variables like recruitment strategy and candidate evaluation. But permutation importance is an indication of predictive dependence and not causal dependence or how much a variable is desirable to use in hiring decisions. It also depends on the model configuration and synthetic data set that is selected.

4.4. Model Robustness, Calibration, and Fairness Assessment

The robustness test indicated that the XGBoost was stable when numbers were perturbed reasonably when using the XGBoost. However, further missingness generated bigger decreases in classification performance showing sensitivity to missing recruitment data.

Table 4. Robustness, Calibration, Bootstrap Confidence Intervals, and Subgroup Performance of the Selected Recruitment Model.

Assessment	Accuracy	F1-score	ROC-AUC
Original testing data	0.9300	0.8757	0.9311
Numerical noise (5%)	0.9267	0.8690	0.9280
Numerical noise (10%)	0.9067	0.8293	0.9262
Additional missingness (5%)	0.9000	0.8148	0.8909
Additional missingness (10%)	0.8800	0.7831	0.8897
Bootstrap 95% CI — baseline	0.8967–0.9567	0.8140–0.9247	0.8843–0.9672

Additional calibration results: Brier score = 0.0675; expected calibration error = 0.0530; log loss = 0.2622. The 500-replication bootstrap was the one that suggested that the conditional uncertainty intervals were minute. The demographic parity gap of the subgroup analysis (exploratory) of the data with the binary coding of the gender was 0.0732, equal opportunity gap 0.0802 and the false-positive-rate gap 0.0001. These values reflect quantifiable variations in model results but not discriminatory conduct nor do they reflect adherence to equal opportunity in recruitment standards.

4.5. AI Adoption Opportunities, Challenges, and Managerial Strategy Framework

The results of the computations were used to design a proposed managerial model of AI-enabled talent acquisition. The framework focuses on predictive recruitment support, data-quality management, algorithmic transparency, organizational-ready, and human supervision. Notably, there were no Gujarat-specific survey answers to be had; so, the strategies below are not analytically informed recommendations but analytically verified regional adoption results.

In a possible application to the service sectors of Gujarat, the technical results are converted to the suggested managerial interventions and not quantifiable regional results. An initial implementation plan would include evaluation of the quality of HR data and organizational preparedness, prediction model testing using locally

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ISSN: 2208-2190 Pages- 70-82
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gathered data, audit of explanation and subgroup results, and leaving the selection based on consequential decisions to human analysis. These measures were not experimented on Gujarat employers and no adoption rates or effect by region can be drawn using the synthetic dataset.

Table 5. AI Talent Acquisition Adoption Opportunities, Implementation Challenges, and Proposed Managerial Strategies in Gujarat's Service Industries.

Opportunity	Challenge	Proposed Managerial Strategy	Supporting ML Evidence
Predictive recruitment support	Generalization to real candidates	Conduct local validation before deployment	XGBoost test F1 = 0.8757
Explainable candidate assessment	Dependence on specific predictors	Review feature relevance and interpretability	Strategy importance = 0.2414
Data-driven recruitment operations	Missing or incomplete information	Establish data-quality controls	F1 declined to 0.7831 under 10% added missingness
Responsible AI implementation	Subgroup disparities	Implement fairness monitoring and human oversight	Equal opportunity gap = 0.0802
Organizational adoption planning	Unverified regional readiness	Conduct Gujarat HR surveys and organizational pilot studies	Regional validation unavailable

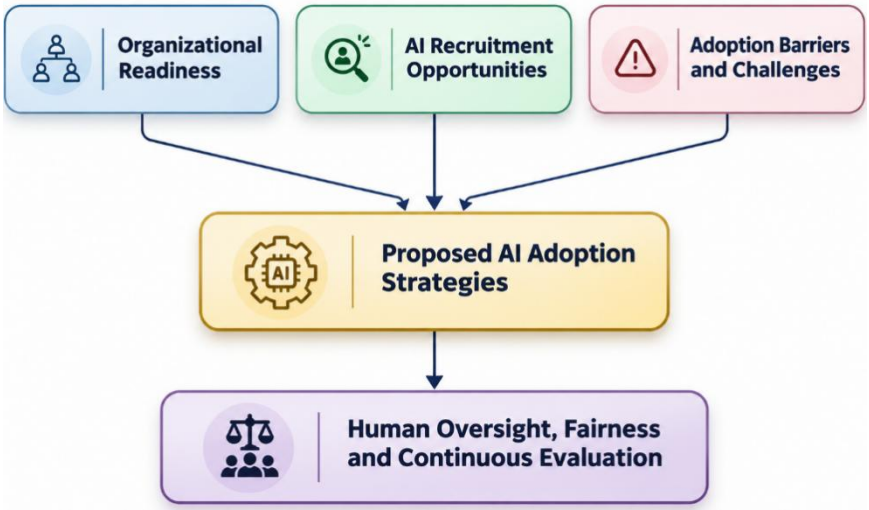

Figure 5. Proposed AI-Enabled Talent Acquisition Adoption Framework for Gujarat's Service Industries.

The conceptual adoption model is combined in figure 5 which incorporates organizational preparedness, possible recruitment advantages, barriers to implementation, and accountable governance. The results show that it is technically possible to model the recorded hiring outcomes in the synthetic data and there are considerations that need to be investigated prior to the implementation in the service industries of Gujarat. Practical efficiency or willingness to embrace must be determined, though it has to be proven outside, genuine recruitment examination and nearby company support.

5. Discussion

The findings point to the possibility of the machine-learning-based recruitment analytics making systematic hiring decisions and revealing important disparities between predictive accuracy, interpretability, and applicability to organizations. Analysis of 1,500 records of synthetic candidates identified a high level of statistically significant relationships between the results of hiring and recruitment-based variables, in particular, the kind of recruitment strategy, level of education, assessment of the skills, personality, success in the interview and work experience. There were six predictors that were statistically significant when false

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discovery rate was adjusted. Among the interesting observations is the fact that the results of the hiring are most strongly linked to the recruitment strategy, which implies that it is the encoded selection strategy in the center of the patterns of decisions that are observed in the data. However, these associations define the data of synthetic recruitment and cannot identify causal relationships and actual organizational hiring behavior.

The ensemble learning was found to work well in the recruit classification, as compared analysis of Logistic Regression, Random Forest, and XGBoost revealed. XGBoost was chosen as it had the best training-only cross-validation F1-score (0.8691) with a held-out test accuracy of 93.00, a precision of 97.37, a recall of 79.57, an F1-score of 87.57, and a ROC-AUC of 0.9311. Random Forest however scored slightly higher on the held-out F1-score (0.8772 as compared to 0.8757) and ROC-AUC (0.9320 as compared to 0.9311); therefore, the choice of XGBoost cannot be construed to imply higher performance on all test scores. Of utmost importance is the difference between precision and recall: positive hiring predictions were reliable overall, but an estimated one-fifth of the positive cases were not identified. This observation shows the shortcomings of using accuracy as a measure of recruitment decision support. Past studies have also shown that good predictive performance is not always a predictor of fair and reasonable selection decisions (Köchling et al., 2021).

The interpretability analysis may also be seen as an extra contribution since it allows determining the variables that have the greatest impact on the predictions of the chosen model. The biggest mean permutation-importance score (0.2414 ROC-AUC decrease) was produced by recruitment strategy, which is significantly higher than the mean permutation-importance score of personality (0.0514), educational level (0.0504), interview score (0.0449), and skill score (0.0397). This predictive importance concentration demonstrates that the model depends a lot on the encoded recruitment strategy of the dataset. It also brings out a significant governance issue: whether the recruitment strategy reflects existing selection rules, this model can replicate the rules instead of defining the suitability of a given candidate on its own. Past researchers decided that machine learning holds promise to extract predictive information based on attributes of the applicants (Sajjadiani et al., 2019). The present results are based on this modeling perspective; they are a compound of model comparison and model predictor level interpretation, but the permutation importance measures are measures of predictive dependence and not cause.

The strength test also provided that predictive performance could not be as good when simulated data-quality noise was used. The accuracy decreased to 88.00% at 10 percent more missingness than 93.00% when it was tested regularly and the F1-score reduced to 78.31. Brier score (baseline) of 0.0675 and the calibration error which is supposed to be 0.0530 also indicates the quality of probabilistic prediction. This shows that predictive ability and robustness to degradation in input-data can be exchanged, and it is this fact that warrants the importance of data control and operational checking. This discussion is in line with the works that concentrate on the multifacetedness of AI potentials, administrative skills, and organizational control in HRM (Úbeda-Garcia et al., 2025).

There are three main implications of the findings. Firstly, the recruitment analytics should aid human judgement and not automatically make decisions regarding employment results. Second, the explanations should be given along with the predictive suggestions to promote the examination and responsibility of the model. Third, stability of performance, calibration and fairness should be checked by organizations before being implemented. Analysis using permutation offers helpful model-level explanation, but correlated predictors and relationship specific to the dataset might affect rankings of importance (Altmann et al., 2010).

Applicability of the research to service industries in Gujarat on a regional basis as well as implications to managers. The results are used to give a conceptual foundation to think about AI-based talent acquisition in service-based, futuristic, and informational technology, banking, health, hospitality, and retail. The experiments were based on the synthetic and nonregional recruitment data but the predictive dependence on the recruitment strategy and the measures of candidate-assessment reveal that the managers ought to initially guarantee the relevance, provenance and equity of their own recruitment information. The lowered performance of the models when simulated missingness occurs further promotes local checks on data-quality and ongoing performance checks. An accountable potential adoption routeway would be a blend of organizational preparedness evaluation, HR personnel training, comprehensible model results, when suitable, subgroup audits, and human-controlled choice. The suggestions are analytically based and have not been tested in the Gujarat state thus the suggested framework will need to be put into practice via the methods of carrying out regional HR surveys, organization case studies or actual records of the recruitment process to determine the effectiveness on-the-job.

There are several shortcomings in the research. The data is artificial, has only 1,500 observations and is not reflective of proven recruitment practices within service industries in Gujarat. External validation of the adoption and survey of the region was not done. The other limitation of subgroup fairness was that the features utilized, and the proposed adoption model were not implemented in a practical recruiting situation. Future studies should include actual histories of multisector recruiting, validation and prospective organizational

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survey and harsh measures of fairness besides a human-in-the-loop evaluation. The extensions would be used to ascertain whether the proposed analytical model would advance the reality on the ground hiring decisions, without compromising the transparency, equity and accountability.

6. Conclusion

This paper has discussed how predictive machine learning can be used to combine explainable analytics with predictive machine learning to support recruitment decisions, which are accurate, interpretable, and reliable, and that it can be applied to organizational decisions. It developed an analytical framework, which was structured and used 1,500 synthetic candidate records, including data preprocessing, statistical analysis, comparative classification, and permutation feature importance, calibration assessment, and robustness evaluation. Logistic Regression, random forest, and XGBoost were considered to determine how well each is suitable to predict hiring. XGBoost has been chosen based on the largest training-only cross-validation F1-score, with test accuracy of 93.00, F1-score of 87.57 and ROC-AUC of 0.9311. The strongest predictor was the recruitment strategy, and robustness testing revealed the worsening performance with the increase in the missingness. These results will mean that predictive effectiveness will be determined using interpretability, data quality and operational reliability. The combination of the analytical prediction of recruitment methods, prediction description of features, and evaluation of robustness and a proposed human-oriented decision-support system is the key innovation. This mixture offers the methodological basis of apprehending algorithmic suggestions of hiring and not to overlook managerial decision-making. The use of artificial data, small sample size and lack of external organization validation limit the generalizability of the results though. Future studies need to take into consideration actual recruitment data, cross-organizational verification, fairness auditing, and prospective human-in-the-loop analyses to find out whether the framework enhances viable recruitment choices. In conclusion, implementing AI in a responsible way presupposes a balance between predictive performance and transparency, accountability, and human control.

In Gujarat service industries, the proposed framework offers an initial, context-specific, framework to evaluate the opportunity, organizational readiness, challenges, and responsible adopting plans to AI-assisted hiring. Its practical usefulness is yet to be proved in Gujarat: additional studies need to be performed to implement the framework to real-life regional recruitment data and organizational data and then draw conclusions about its implementation or the quality of its decision.

References

1. Altmann, A., Toloşi, L., Sander, O., & Lengauer, T. (2010). Permutation importance: A corrected feature importance measure. Bioinformatics, 26(10), 1340–1347. https://doi.org/10.1093/bioinformatics/btq134
2. Bankins, S. (2021). The ethical use of artificial intelligence in human resource management: A decision-making framework. Ethics and Information Technology, 23, 841–854. https://doi.org/10.1007/s10676-021-09619-6
3. Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32. https://doi.org/10.1023/A:1010933404324
4. Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 785–794. https://doi.org/10.1145/2939672.2939785
5. Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodríguez-Espíndola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. Human Resource Management Review, 33(1), Article 100899. https://doi.org/10.1016/j.hrmr.2022.100899
6. Dadaboyev, S. M. U., Abdullayeva, J., Abbosova, N., Suleymenova, A., & Mamadjanova, K. (2025). Role of artificial intelligence in employee recruitment: Systematic review and future research directions. Discover Global Society, 3, Article 99. https://doi.org/10.1007/s44282-025-00246-w
7. El Kharoua, R. (2024). Predicting hiring decisions in recruitment data [Data set]. Kaggle. https://www.kaggle.com/datasets/rabieelkharoua/predicting-hiring-decisions-in-recruitment-data
8. González-Morales, A., Martín-López, M. M., & Góngora-Larequi, F. (2026). A systematic review and descriptive analysis of artificial intelligence applied to recruitment and personnel selection in the present and possible future. Discover Artificial Intelligence, 6, Article 762. https://doi.org/10.1007/s44163-026-01488-6
9. Herold, M., & Roedenbeck, M. R. H. (2025). AI-driven research in the recruitment and selection process: Application of an AI taxonomy with a systematic literature review. SAGE Open, 15(3), 1–21. https://doi.org/10.1177/21582440251361746
10. Jatobá, M. N., Ferreira, J. J., Fernandes, P. O., & Teixeira, J. P. (2023). Intelligent human resources for the adoption of artificial intelligence: A systematic literature review. Journal of Organizational Change Management, 36(7), 1099–1124. https://doi.org/10.1108/JOCM-03-2022-0075

Vol. 12 Issue 7s (November, 2026)
ISSN: 2208-2190 Pages- 70-82
DOI: https://doi.org/10.69023/rs8bky20

11. Köchling, A., & Wehner, M. C. (2020). Discriminated by an algorithm: A systematic review of discrimination and fairness by algorithmic decision-making in the context of HR recruitment and HR development. Business Research, 13(3), 795–848. https://doi.org/10.1007/s40685-020-00134-w
12. Köchling, A., Riazy, S., Wehner, M. C., & Simbeck, K. (2021). Highly accurate, but still discriminatory: A fairness evaluation of algorithmic video analysis in the recruitment context. Business & Information Systems Engineering, 63, 39–54. https://doi.org/10.1007/s12599-020-00673-w
13. Köchling, A., Wehner, M. C., & Warkocz, J. (2023). Can I show my skills? Affective responses to artificial intelligence in the recruitment process. Review of Managerial Science, 17, 2109–2138. https://doi.org/10.1007/s11846-021-00514-4
14. Mori, M., Sassetti, S., Cavaliere, V., & Bonti, M. (2025). A systematic literature review on artificial intelligence in recruiting and selection: A matter of ethics. Personnel Review, 54(3), 854–878. https://doi.org/10.1108/PR-03-2023-0257
15. Ore, O., & Sposato, M. (2022). Opportunities and risks of artificial intelligence in recruitment and selection. International Journal of Organizational Analysis, 30(6), 1771–1782. https://doi.org/10.1108/IJOA-07-2020-2291
16. Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2022). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. The International Journal of Human Resource Management, 33(6), 1125–1147. https://doi.org/10.1080/09585192.2021.1879206
17. Pessach, D., Singer, G., Avrahami, D., Chalutz Ben-Gal, H., Shmueli, E., & Ben-Gal, I. (2020). Employees recruitment: A prescriptive analytics approach via machine learning and mathematical programming. Decision Support Systems, 134, Article 113290. https://doi.org/10.1016/j.dss.2020.113290
18. Pillai, R., & Sivathanu, B. (2020). Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations. Benchmarking: An International Journal, 27(9), 2599–2629. https://doi.org/10.1108/BIJ-04-2020-0186
19. Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2020). Mitigating bias in algorithmic hiring: Evaluating claims and practices. Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency, 469–481. https://doi.org/10.1145/3351095.3372828
20. Sajjadiani, S., Sojourner, A. J., Kammeyer-Mueller, J. D., & Mykerezi, E. (2019). Using machine learning to translate applicant work history into predictors of performance and turnover. Journal of Applied Psychology, 104(10), 1207–1225. https://doi.org/10.1037/apl0000405
21. Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. California Management Review, 61(4), 15–42. https://doi.org/10.1177/0008125619867910
22. Úbeda-García, M., Marco-Lajara, B., Zaragoza-Sáez, P. C., & Poveda-Pareja, E. (2025). Artificial intelligence, knowledge and human resource management: A systematic literature review of theoretical tensions and strategic implications. Journal of Innovation & Knowledge, 10(6), Article 100809. https://doi.org/10.1016/j.jik.2025.100809
23. Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. The International Journal of Human Resource Management, 33(6), 1237–1266. https://doi.org/10.1080/09585192.2020.1871398